Three Essays on Relationships in International Trade

by

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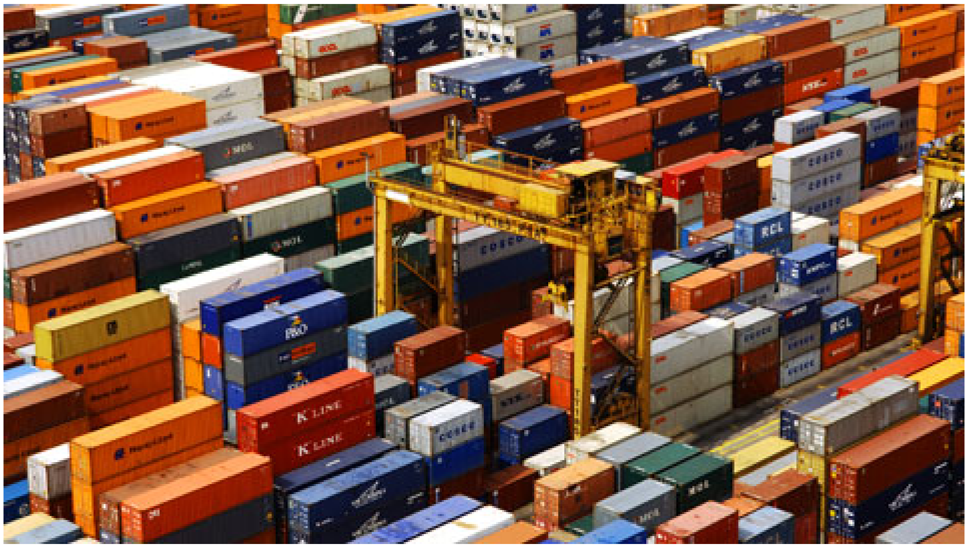
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For Iris

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ABSTRACT

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Chair: Andrei Levchenko

In a time of greatly improved long-distance transportation technology, low tariffs, and continued strengthening of economic links between countries, scholars of international trade have turned to their attention to factors influencing companies that take part in international business. This dissertation consists of three studies that explore how relationships these firms have with other firms around the world influence trade flows and prices, as well as company-level employment, wages, output, and which products to buy.

The first chapter, "It's Not You, It's Me: Breakups in U.S.-China Trade Relationships" uses confidential U.S. Customs data on U.S. importers and their Chinese exporters to investigate the frictions from changing exporting partners. High costs from switching partners can affect the efficiency of buyer-supplier matches by impeding the movement of importers from high to lower cost exporters. I test the significance of this channel using data which identifies firms on both sides of an international trade relationships. I propose and structurally estimate a dynamic discrete choice model of exporter choice. Halving switching improves match efficiency and leads to a 12.5% decrease in the U.S.-China Import Price Index.

The second chapter, "Gains from Offshoring? Evidence from U.S. Microdata", joint with Jooyoun Park and Jagadeesh Sivadasan, assesses how offshoring impacts domestic firm-level aggregate employment, output, wages and productivity. Offshoring firms are on average larger and more productive compared to non-offshorers. However, we find that offshorers suffer from a large decline in employment and output relative to their peers even in the long run.

The third chapter, "Learning and the Value of Relationships in International Trade", joint with Tim Schmidt-Eisenlohr, explores the value to firms of being in relationships. Over half of the time importers adjust their source for a product, it is to a "familiar" exporter, meaning either an exporter used for that same product previously, or to one used for separate product purchases. 43% of new product purchases also come from familiar exporters. These results point to the importance of reputation and information asymmetries. We explore this channel through a model of supplier learning, creating estimates for the extent to which relationships influence trade flows.

CHAPTER I

'It's Not You, It's Me': Breakups in U.S.-China Trade Relationships

1.1 Introduction

An influential literature has studied the effects of misallocated resources on aggregate productivity: major improvements in productivity could theoretically be achieved by raising the marginal products of capital and labor of producers in developing countries to U.S. levels (Hsieh and Klenow 2009). However, a firm matching with a suboptimal supplier is another source of potential inefficiency, in particular if the supplier being used has high prices or poor quality. An anecdote illustrates that buyer-supplier mismatches are a significant bottleneck in international trade. In 2008, David Wei, CEO of e-commerce giant Alibaba.com announced a "Gold Supplier" identification program in order to clearly flag reliable exporters in China, with the explicit goal of making foreign sourcing decisions easier.[1] However, three years later, wide-scale fraud under this program came to light, resulting in Wei's resignation.[2] That a behemoth like Alibaba.com was both aware of the difficulties involved

[1] "[T]he initiatives we announced today are aimed at ... accelerating user growth and customer acquisition. Our Quality Supplier Program will allow buyers to trade with greater confidence while the Gold Supplier Starter Pack will appeal to a wide range of potential new customers." – David Wei, CEO, Alibaba.com, 11/3/2008

[2] "Alibaba ... reported that 2,326 high volume sellers who pay a fee to the company to peddle their wares on the site - 'gold suppliers', as they're called- defrauded customers over the course of

for buyers matching with suppliers and unable to resolve them in a satisfactory way demonstrates that finding the right supplier is not easy. If an importer is unaware of identical but lower-priced alternatives to its current supplier, or unwilling to bear the costs and uncertainty involved in such a change, then this creates the potential for inefficiency. Testing the importance of this channel is challenging, however, as data on relationships between final producers and their suppliers is sparse.

This paper utilizes confidential U.S. Customs and Border Protection data on U.S. importers and their Chinese exporting partners to explore the costs involved in changing partners and their impact on import prices. The database includes information for firms on both sides (U.S. and foreign) of an international trade transaction, allowing the study of these "switching costs" for U.S. importers. Empirical results indicate that such costs are likely to be substantial: from 2003-2008, 45% of arm's-length importers maintain their partner from one year to the next, even with an average of 35 available exporters selling the same product.[3] Nearly half of the total value of U.S. imports from China is concentrated among those importers who used the same exporter year-to-year. Furthermore, there is remarkable geographic inertia among importers who do change their partner: one-third of all switching importers remain in the same city as their original partner, even with an average of nine available cities to purchase their product. Finally, importer switching decisions are correlated with prices: those importers who paid the highest prices are much more likely to change their partner. Thus there is reason to believe in the potential for efficiency gains by reducing frictions to importer switching.

Guided by the above empirical regularities, I develop a dynamic discrete choice model of exporter choice. The importing firm decides which exporter to use by

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two years, with the assistance of nearly 100 Alibaba.com employees... As a result of the scandal, Alibaba.com CEO David Wei, and his deputy, COO Elvis Lee, both resigned yesterday." – Fortune Magazine, 2/22/2011

[3]I use the term importer to refer to a *firm-HS10 product pair*. Thus a firm that imports two HS10 products is considered to be two separate importers. HS10 is a ten-digit product code, the most disaggregated product code used by U.S. firms.

comparing partner-specific profits across all possible choices, including its current match. Considerations of which exporter to use depend not only on the price and quality of each exporting firm, but also per-unit switching costs, both at the partner and the city level. The key tradeoff that the firm faces is that switching to either a cheaper or a higher quality exporting partner raises profits, but changing one's current exporter or geographic location is costly. The model produces closed-form expressions of choice probabilities for each potential outcome, which allows computation of the switching cost parameters via maximum likelihood. I compute exporter quality using a procedure similar to the "control function" estimator of unobserved heterogeneity from Kim and Petrin (2010) and the quality ladder estimation of Khandewal (2010). I then use the Mathematical Programming with Equilibrium Constraints (MPEC) techniques developed by Dubé, Fox and Su (2012) and Su and Judd (2012) to solve the model. I estimate the parameters of the model industry-by-industry.

The main quantitative results can be summarized as follows. First, model estimates of switching costs are large, heterogeneous across industries, and match the underlying data well. Based on model estimates, in order to be indifferent between its current partner and another partner in the same city charging the same price, the average importer would require a positive shock to profits of two standard deviations higher than average from the new partner. Industries with low switching costs have high amounts of switching, and products that are less substitutable tend to have higher switching costs. Second, the impact of switching frictions on importer prices is sizable. Using a randomly selected sample of 50 industries, I perform the following counterfactual: match importers with different exporters by altering switching cost parameter values, then construct the U.S.-China Import Price Index to determine aggregate price changes arising from these new matches. I find that reducing frictions by half reduces the Import Price Index by 12.5%, a reduction achieved by shrinking the percent of staying importers from 57% to 18%. Thus there is a substantial efficiency gain involved in lowering the cost of switching export partners. On the other hand, tripling the barriers to switching results in a 7.62% increase in the Import Price Index, and 90% of importers remain with their partner year-to-year. Third, changing one friction without changing another has differential effects on prices. Eliminating geographic frictions while maintaining partner switching costs reduces the Import Price Index by 7.37%. However, keeping only the geographic switching cost reduces prices by 15.20%. Finally, I estimate the trade flow to a newly available supplier which is not subject to any geographic switching friction from the same random sample of industries. If that supplier charges the median price among Chinese exporters within its product category and produces a high-quality variety, this collection of prospective suppliers (one per industry) would be able to attract approximately 4% of all imports from China. A supplier that can be switched to without geographic frictions is one way to consider a potential new U.S. supplier, but the median price among Chinese exporters is approximately 57% lower than the price charged by U.S. exporters for the same product mix. This demonstrates that there are substantial barriers to "re-shoring" Chinese imports back to U.S. suppliers.

The results described above demonstrate a significant effect of switching costs on exporter choice and import prices. There are a number of interpretations for what these switching costs represent. Allen (2012) shows the importance of information frictions, especially geographically, for Filipino farmers searching for buyers of their product. Thus one way to view the high cost of switching partners and additional cost of geographic switching is that importers are simply not aware of other low-price options that are available. A policy that reduces switching frictions is one that would reduce information asymmetry, such as a"gold standard" directory of all available exporters and prices put forth by both the U.S. and China, or the creation of an exporter marketplace for importers to utilize and select partners. A second interpretation is the existence of long-term trading contracts such as in Kleshchelski and

Vincent (2009), that reduce uncertainty in product prices, quality, or lead time, but prevent more efficient matching. In this dimension, an overall improvement in contracting institutions leading to more widespread use of short-term contracts would be consistent with reductions in switching costs discussed above. A third explanation for high switching costs is related to the overall logistical difficulty in adjusting one's suppliers in response to short-term changes in purchasing prices even with knowledge of other alternatives and a freedom to use them, as in Drozd and Nosal (2012). Here, the experiments described above are best thought of as more widespread use of intermediaries- companies specializing in connecting importers with exporters. Indeed, intermediaries play an important in the Chinese export market, as described in Ahn, Khandewal, and Wei (2011) and Tang and Zhang (2012). In summary, the above quantitiative exercises have direct interpretations, and the result of policies that reduce matching frictions will be a significant improvement in productive efficiency at the firm level.

Although the field of international trade has focused on numerous aspects of firm-level participation in international activity, including especially the decision to export, import, engage in FDI, or use intermediaries, the study of individual exporter-importer relationships remains relatively sparse. Empirical work on this question began with the study of networks in international trade: Rauch (2001) surveys the potential for transnational cultural networks to help smooth international trade and reduce barriers to entry, while Rauch and Watson (2004) present a general equilibrium model through which economic agents can use their supply of networks to either produce/export more efficiently or to become an intermediary. Recent work has made use of the U.S. Customs database used in this work, which provides information about U.S. importers and their foreign exporting partners. Eaton et. al. (2012) study the relationship between Colombian exporters and the number of U.S. importers they partner with over time and calibrate a search and matching model to match exporter decisions, including sales, number of clients, and transition probabilities. Kamal and Krizan (2012) use U.S. Census trade transaction data to document trends in the formation of importer-exporter relationships. Kamal and Sundaram (2013) use the same U.S. import data to determine how likely textile producers in Bangladeshi cities are to follow other exporters in their same city to export to a particular partner. They find "importer-specific" spillovers are an important part of the general information spillovers that characterize exporting. Each of these puts the onus on the exporter to undertake searching behavior buyer by buyer, while I model matching as an importer's choice given information about each exporter. Other work takes advantage of two-sided trade data to study the effects of heterogeneity on trade: Bernard, Moxnes, and Ulltveit-Moe (2013) develop a model of relationhip-specific fixed costs to exporting using Norwegian buyer-supplier trade data, while Blum, Claro, and Horstmann (2010) use exporter-importer pair data on Chile to study the effects of intermediaries. Alessandria (2009) is a model of search frictions in international trade that, like my model, generates deviations from the law of one price, without distinguishing importers within a country. Kleshchelski and Vincent (2009) also construct a model of switching frictions, where firms and customers form long-term relationships, showing that prices stabilize as the number of repeat buyers increases. Antràs and Costinot (2011) and Petropoulou (2011) model the effects of trade with costly search frictions, and Allen (2012) estimates a buyer search model on agricultural trade inside the Philippines. I combine the theory of partner choice with data on importer-exporter relationships and geographic location, through which I am able to determine the effects of switching frictions on import prices.

The way I measure these frictions is with a structural demand model that incorporates the factors underpinning importer-exporter switching behavior, including geographic components. To do this, I use a model of dynamic discrete choice, pioneered by Rust (1987) in his study of bus engine replacement. I implement the problem in a similar way, using the Mathematical Programming with Equilibrium Constraints (MPEC) methodology for solving discrete choice problems found in Su and Judd (2012) and Dubé, Fox, and Su (2012). As in those studies, my model includes costs entering into a firm's profit function, where in my case, the costs are supplier switching costs at both the partner and city level. Estimates are retrieved through maximizing a likelihood function based on observed outcomes for importer-exporter switching. The model I estimate is most similar to the model of employer choice utilized by Fox (2010) in his study of Swedish engineers. Similar to the use of wages as a driving force behind employee switching behavior, in my context, one of the main components of the "stay or switch" decisions is the price offered to U.S. importers by a Chinese supplier. The model also shares some similarities with Lincoln and McCallum (2012), who produce estimates of exporting fixed costs that broadly measure the frictions involved in entering the export market that are comparable across industries. More generally, there have been a number of studies that estimate the effects of relationship networks in other contexts: Joskow (1985) studies contract length among coal suppliers and power plants, while Atalay, Hortacsu, and Syverson (2012) measure the extent to which firms rely on subsidiaries versus outside firms for intermediate input purchase. Egan and Mody (1992), and Kranton and Mineheart (2001) present models on the formation of buyer-seller networks and how the properties of these networks affect economic outcomes.

The rest of the paper is organized as follows. Section 1.2 describes the data sources used in this paper and summarizes the empirical results. Section 1.3 presents the dynamic discrete choice model with supply chain adjustment costs. Section 1.4 describes the implementation of the model and summarizes the baseline results. Section 1.5 describes the quantitative experiments used to determine the importance of the supplier-switching channel. Section 1.6 concludes.

1.2 Data and Stylized Facts

1.2.1 Importer-Exporter Data

The database I work with is the Longitudinal Foreign Trade Transaction Database (LFTTD), which contains confidential information on all international trade transactions by U.S. firms, and is maintained jointly by the U.S. Census Bureau and U.S. Customs. Every transaction of a U.S. company importing or exporting a product requires filing a form with U.S. Customs and Border Protection, and the LFTTD contains the universe of these transactions. In particular, the import data consists of all the information included in customs documents provided by U.S. firms purchasing goods from abroad, including quantity and value exchanged for each transaction, HS 10 product classification, date of import and export, port information, country of origin, and a code identifying the foreign supplier firm. Known as the *manufacturing ID*, or *MID*, the foreign partner identifier contains limited information on the name, address, and city of the foreign supplier.[4] Through a variety of "external vailidity" checks outlined in Appendix 1.A, I find substantial support for the use of the MID as a reliable, unique identifier, both over time and in cross-section. I use this variable to provide stylized facts for the amount of churning in U.S.-China trade relationships and the geographic elements of switching behavior.[5]

At this stage, I perform an initial cleaning of the LFTTD, using methods outlined in Bernard, Jensen, and Schott (2009) and Pierce and Schott (2009). As in

[4]Specifically, the MID contains the first three letters of the producer's city, six characters taken from the producer's name, up to four numeric characters taken from its address, and the ISO2 code for the country of origin.

[5]The results below depend on the validity of the MID as both a cross-sectional unique identifier and as a panel variable tracking foreign exporters over time, which I check using external data. Separately, one may also be concerned about whether U.S. firms are constructing the MID as required - what I call "internal validity" - with potential issues including miscoding, unclear rules for construction, or the possibility of capturing intermediaries rather than firms actually producing the traded product. For this reason, I undertake an in-depth exploration of this variable, including its construction, the relevant laws surrounding information provided in trade transactions. These issues are also explored in Appendix 1.A.

Bernard, Jensen and Schott (2009), I drop all transactions with imputed quantities or values (which are typically very low-value transactions) or converted quantities or values. I also eliminate all related-party transactions, as exporters who are importing from separate branches of the same firm will likely have very different relationship dynamics than arm's-length exporters. I concord HS codes over time according to the methodology in Pierce and Scott (2009). In addition, I clean up unreasonable values for the MID specifically related to U.S.-China trade. I restrict the sample to importers with a firm country identifier of China (meaning the producing firm is located in China). Due to the entrepôt nature of Hong Kong's international trade flows, I concentrate solely on Mainland China - deleting any observation that has any appearance of coming from Hong Kong, Macau, or Taiwan. For example, a city code of "HON", even with a country code for mainland China, is likely referring to Hong Kong and thus dropped.[6] Finally, I drop any firm that has a three-letter city code that is not in the top 300 cities of China by population.

1.2.2 Stylized Facts

The starting point of my analysis is to use the exporting partner MID to illustrate the extent of partner-switching. My unit of observation is a U.S. importer (firm-HS10 product combination). Some importers have more than one exporter, so I define an importer's *main exporter* in any time period to be the one from which the largest percentage of imports were delivered[7]. I define a firm as "staying" with one's partner

[6]Other dropped city codes: "KOW" for Kowloon, Hong Kong; "MAC" for Macau; "AOM" for the Chinese Pinyin spelling of Macau, "Aomen"; "KAO" for Kaohsiung, Taiwan.

[7]This simplification introduces the potential for "false switching", where an importer uses the same exporter in two periods, but changes the source of the plurality of its imports. Analysis of the LFTTD indicates that U.S. importers typically import a very large share of their total imports from only one partner. The average share of imports that come from a U.S. importer's main Chinese partner is 83.9%, with a standard deviation of 22%. Furthermore, multiple importers do not dominate in the data. Kamal and Krizan (2012) present some basic statistics on the number of exporting relationships that a U.S. importer may be in: across all U.S. importers, the average number of exporting partners for a U.S. importer is 1.8, and the average number of exporting partners for a "polygamous" U.S. importer is 4.

if its main exporter remained the same over time[8]. I track the universe of U.S. importers from China in 2003-2008, and determine whether they (a) also imported one year previously, and if so, (b) whether they continued to import from the same exporting partner or geographic location as in the previous year. Figure 1.1 plots the fraction of importers staying with their partner, staying in the same city, and staying in the same province.

Two facts are clear from Figure 1.1. First, there is a significant share of U.S. importers who maintain the same partner over time. Even though the number of potential exporting choices is increasing over this time period, the share of importers using the same supplier is 45.9% over this time. As a benchmark, given that there are an average of 30 Chinese exporters to the U.S. per HS10 product in the data, if importers were choosing their partners randomly each year, the probability of switching partners would be 29/30, or 97%. Thus path dependence is far higher than would be expected if importers were choosing their partner randomly. These staying importers account for 44.9% of the total value of arm's length imports from China over this time period, which shows these are not simply very small importers who are switching. Secondly, among those firms who do choose to switch, approximately one-third of all importers remain in the same city as their original partner. Using the same benchmark as above, random exporter selection would imply an 86% chance of switching city.[9] Thus there is strong inertia keeping firms in their original city, even if they choose not to use the same exporting partner as before. There are many

[8]All results are robust to different definitions of "staying", including staying with any one of the set of partners, or staying with the entire set of one's partners.

[9]There is an average of 9 cities for each HS10 product, but the number of exporters are not distributed equally across cities. I thus compute the probability of switching city for any one importer in the data if they were choosing their partner with the following formula:

$$Pr\left(CSwitch\right) = \frac{\sum_i \sum_c M_{ic}\left(1 - \frac{X_{ic}}{\sum_c X_{ic}}\right)}{\sum_i \sum_c M_{ic}}$$

where product i and city c have M_{ic} importers and X_{ic} exporters. The term in parentheses is the probability of an importer in city c switching city, which I then weight by the number of importers in that city. The denominator is the total number of U.S. importers from China.

potential explanations for such a finding, including local network formation, efficient distribution channels centered on a particular geographic location, or agglomeration on the export side. In sum, the year-to-year figures show that supplier choices are highly correlated with previous supplier usage, and decisions of whom to switch to are highly dependent on geographic considerations. It is these stylized facts related to switching, both geographically and over time, that govern the dynamic discrete choice model I lay out in Section 1.3.

The stylized facts about importer-exporter relationships described above are robust to a number of alternative checks and specifications. Firstly, Figure 1.2 shows that the tendency to stay with one's exporting partner is not concentrated among only small or large importers: even as the share of total imports from China increases dramatically from 2003-2008, the share of imports from importers keeping their same partner remained at about 40-45% of total imports, very similar to the overall share of importers remaining with their partner. Secondly, one may be concerned that switching is driven by exit on the exporter side: given the structural changes in the Chinese economy over this period, including entry into the WTO, it is likely that many exporters are entering or exiting. To eliminate this channel, I recreate the results using only those matches where the exporting MID is found in both years. These results are found in Figure 1.3 Panel A. Mechanically, the percentage of firms staying with their partner must increase, but the two main stylized facts described above carry over: a significant share of (but not all) importers stay with their partners, with previous geographic location an important factor in the decision of where switching importers move to. I also check that the results are not driven by my definition of an importer as a *firm-HS10 product* combination. Indeed, it is possible for one firm to appear multiple times in Figure 1.1. In particular, if one firm imports multiple products, then the counts may exaggerate or understate the effects of firm switching behavior. I thus perform the same decomposition considering a *firm* as the unit of analysis, rather than a *firm-HS10 product* combination. Even with this much more sparse assignment of switching firms, Figure 1.3 Panel B shows that the results remain very similar: now, close to two-thirds of continuing importers stay with their partners, with considerable geographic stickiness. These stylized facts are robust to a number of other specifications, including using only importing firms classified as manufacturing firms, an importer defined as a firm-HS6 product combination, individual year trends, different definitions of switching, and the share of importers not adjusting their supply network over a longer time frame than one year. These are described in greater detail in Appendix 1.B.

1.2.3 Reduced-Form Regression Results

I next analyze the factors that govern the stay-or-switch supplier decisions. There are a number of potential explanations for switching behavior that I can measure using the LFTTD data. Using U.S.-China trade data from 2002-2008, I use the following linear probability model to estimate the relationship between the decision of a U.S. importer to switch Chinese exporting partners and a variety of potential explanatory variables, including price, size and age of the Chinese partner, U.S. importer size, and the date of entry into importing.

$$\begin{aligned} Stay^{j}_{i,t,t+1} = \alpha_0 + \sum_{k=1}^{10} \alpha_k \mathbb{1}\left[StandardPriceCat_{i,t} = k\right] + \gamma_1 ExpChar^{j}_{i,t} + \\ \gamma_2 ImpChar^{j}_{i,t} + f_j + f_t + v_{i,t} \qquad (1.1) \end{aligned}$$

As above, I define importer i importing product j as staying ($Stay^{j}_{i,t,t+1} = 1$) with its export partner if it maintains the largest percentage of imports from the same supplier in time t and $t+1$. I define the "standardized price" ($StandardPrice$) to be the "unit value" from the LFTTD, minus its HS10 product mean and divided by the standard deviation. Thus prices are comparable across industries. I allow for non-monotonic effects of price on staying by including it as a categorical variable $StandardPriceCat$ representing each of ten deciles. I omit the 5th decile in the regression, in order to check the effects of having both very low and very high prices. I use both exporter characteristics ($ExpChar$) and importer covariates ($ImpChar$). For exporters, I calculate the "Supplier Size" of a Chinese exporter by summing together its total exports to the U.S., and similarly calculate the "Supplier Age" of a Chinese exporter by calculating the first year a MID appears in the trade data. On the importer side, I constuct importer size by summing together total imports from China, and the first year of its entry into the Chinese import market by calculating its first appearance in the Chinese import data. All of the above covariates are assigned using their values in the prior year, using later year data only to determine whether or not an importer switched exporting partners. Finally, I include HS10 level fixed effects f_j and year fixed effects f_t. The results of the Linear Probability Model (1.1) are reported in Table 1.1. Standard errors are clustered at the HS10 level.

I begin with the effect of price on the partner staying decision. It is clear that the higher the price a firm paid in a previous year, the lower the probability that it would stay with its original (plurality) partner firm. Though the effect is not significant for prices near the middle of the distribution, the results in Table 1 make it clear that the importers who received the highest prices were 2-3% more likely to switch their partner than the omitted group (5th decile). Those importers paying the lowest prices were also more likely to stay with their partner when accouting for importer and exporter characteristics, as can be seen in Columns (2)-(4). Figure 1.4 contains the same story as Table 1, and is generated using the results in Table 1 Column 4. The shaded regions are 99% confidence intervals for the category-specific coefficients. Those importers paying the highest prices are much more likely to switch their partner than those in the middle and low price regions, while those paying the lowest prices are more likely to stay with their partners. Table 2 repeats the analysis simply using price entering the regression linearly, demonstrating again that higher prices make importers more likely to switch.[10]

The effects of the various importer and exporter characteristics are themselves of interest. Table 1.1 makes clear that the older and/or larger a Chinese exporting firm was, the lower the probability that a U.S. importer would switch. In addition, larger U.S. firms were most likely to stay with their partner. Thus there is substantial room for exporter and importer heterogeneity in explaining the staying decision for U.S. importers with their Chinese exporters.

In conclusion, price is an important factor in the decision of an importer to switch partners, especially the magnitude of the price paid in the previous year. Exporter and importer characteristics more generally are also important factors in the decision of whether or not to stay with one's partner. I use these results to guide the modeling of the exporter choice problem below.

[10]The results are unchanged by estimating (1.1) using only one year of data, as I do in Appendix 1.B.

1.3 Model

This section lays out a dynamic discrete choice framework used to model U.S. importer decisions of exporter choice. Different exporters set different prices for the same product j and have heterogeneous quality. Importers of products in that industry make a decision each period about which firm to import from, a decision that is based both on their current exporter and information about other price/quality menus that are available. Switching exporters involves payment of a set of costs, including both an overall switching cost and an additional cost to be paid if an importer finds a new partner in a previously unused city. Each individual exporter of product j at time t is denoted $x_{j,t}$, and exporters are distinguished both by the price they charge $p_{x,j,t}$ and by the quality of their individual variety $\lambda_{x,j,t}$. If importer m chooses the exporter indexed $x_{j,t}$, I denote this match as $x^m_{j,t}$ and the price paid in that match as $p^m_{x,j,t}$.

1.3.1 Importers

Importers are final good producers, and demand for the variety m has a constant elasticity of substitution demand curve.

$$Q_m = Bp_m^{-\sigma}$$

In the above equation, B is a demand shifter, p_m is the final good price for variety m and σ is the elasticity of substitution.

Final good producer m requires J inputs, indexed $j = 1, ...J$, in order to produce its final good, and production of final good is Cobb-Douglas in labor and those intermediates:

$$Q_m = L^{\alpha} \left(\prod_{j=1}^{J} I_j^{\gamma_j} \right)^{1-\alpha}$$

Although the production function and final demand for its variety are fixed, importer m can choose which exporter to use to import its necessary inputs. At time t, final good producer m has a choice of which exporter $x_{j,t}$ to obtain its quantity of input j. By considering all possible exporters in the market, importers are able to make a profit-maximizing decision between exporters. There are a number of components that affect the decision of which exporter to use.

Firstly, importers make a decision based in part on the expected price they will pay from any exporter, $\mathbb{E}\left[p^m_{x,j,t}\right]$. In particular, importers use their previously paid price to form expectations about the price from their original partner, and average price from each other exporter to form expectations about the price from that exporter.[11] Since the expectation differs depending on what partner was used, this expectation is both *importer-specific* (m) and exporter-specific ($x_{j,t}$), which allows the same exporter to charge different prices to different importers. I describe the calibration of this density in the next subsection.

Secondly, there are frictions involved in finding a different supplier in the following period, modeled as an additional component of the price paid. There is a cost that is paid from switching exporters $\zeta_{x,j}$. Reflecting the geographic nature of switching discussed above, I also include an additional geographic cost $\zeta^j_{c,j}$ that is paid if an importer uses a separate partner in a separate city.

I define importer m's expected per-unit cost of purchasing intermediate j from supplier x^j_t at time t, incorporating the frictions involved in searching for a supplier

[11] This assumption allows each firm to observe the entire spectrum of prices, even though the observed data on prices is a selected sample, namely, only successful importer-exporter matches.

in the following manner:

$$\bar{p}^m_{x,j,t} = \mathbb{E}\left[p^m_{x,j,t}\right] \exp\left\{\zeta_{x,j}\ \mathbb{1}\{x^m_{j,t} \neq x^m_{j,t-1}\} + \zeta_{c,j}\ \mathbb{1}\{c^m_{j,t} \neq c^m_{j,t-1}\}\right\} \tag{1.2}$$

where $\bar{p}^j_{x,t}$ is the expected cost from purchasing one unit of the intermediate from seller $x^m_{j,t}$, and the indicator functions are equal to one if an importer picks a different partner x^j_t from its current match x^j_{t-1}, or another different city c^j_t from its current partner c^j_{t-1}. If final good producer m chooses a new partner in the same city (c_{t-1}) as its old partner, then only $\zeta_{x,j}$ is paid, while if an exporter in a separate city is chosen, $\zeta_{x,j} + \zeta_{c,j}$ is paid. This means that the cost of an input bundle will differ depending on what supplier is chosen, not just because of a higher or lower offered price, but also because of costs of switching one's current partner.

Let $X^m_t = \left\{x^m_{j,t}\right\}^J_{j=1}$ be the vector of supplier choices made by importer m for each input $j = 1, ...J$ at time t. Then with wage w, the expected cost of an input bundle for the final good is:

$$c_m\left(X^m_t\right) = w^\alpha \left(\prod_{j=1}^J \left[\bar{p}^m_{x,j,t}\right]^{\gamma_j}\right)^{1-\alpha}$$

Producing one unit of the final good for a final good producer with productivity ϕ requires $\frac{1}{\phi}$ input bundles, each with cost depending on the vector of suppliers X^m_t. I assume that the productivity of a final good producer depends on factors unobserved by the econometrician (such as the quality of the supplier's product) that are particular to its individual supplier match. In particular, productivity for producer m is multiplicative in a common element for that producer and $\lambda_{x,j,t}$, the "quality" of the variety from exporter x.[12]

$$\phi_m\left(X_t^m\right)=\psi_m\prod_{j=1}^{J}\lambda_{x,j,t}^{\nu}$$

The marginal cost of an importer m with productivity ϕ_m is:

$$MC\left(X_t^m\right)=\frac{1}{\phi_m\left(X_t^m\right)}c_m\left(X_t^m\right)\tag{1.3}$$

Maximizing expected profits at time t means that importer m must set the price of their final good optimally and make its vector of exporter choices X_t^m:

$$\pi_t^m=\max_{p_m,X_t^m}p_mQ_m-MC\left(X_t^m\right)Q_m$$

Using the assumption of CES demand, the optimum price of the final good for producer m is a markup over the marginal cost, $p_m=\frac{\sigma}{\sigma-1}MC\left(X_t^m\right)$. Plugging this and our expression for marginal costs (1.3) into the above profits equation gives the following equation:

$$\pi_t^m=\max_{X_t^m}\frac{1}{\sigma}B\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\phi_m\left(X_t^m\right)\right]^{\sigma-1}c_m\left(X_t^m\right)^{1-\sigma}\tag{1.4}$$

Taking logs of (4) implies that the decision of where to obtain input j is additively separable from the choice of where to obtain all other inputs. Doing so, and defining the log expected profits attributable to using input j as $\ln\pi_{j,t}^m$ gives the following

[12] Given the richness of data available, I implement a model that takes explicit account of "quality" considerations, in particular, those characteristics of an exporting firm that are observed by the potential importer, but unobserved by the econometrician and tend to be correlated with the price. I use the control function approach of Kim and Petrin (2010). I specify the estimating procedure in Section 1.4.1.1 below.

expression:

$$\ln \pi_t^m = A + \ln \pi_{j,t}^m + \sum_{k \neq j} \ln \pi_{k,t}^m$$

where

$$\ln \pi_{j,t}^m = \max_{x_{j,t}^m} \nu (\sigma - 1) \ln \lambda_{x,j,t}$$
$$+ (1-\alpha)(1-\sigma)\gamma_j \left[\mathbb{E}\left[\ln p_{x,j,t}^m\right] + \zeta_{x,j} \mathbb{1}\{x_{j,t}^m \neq x_{j,t-1}^m\} + \zeta_{c,j} \mathbb{1}\{c_{j,t}^m \neq c_{j,t-1}^m\}\right] \quad (1.5)$$

and $A = \ln \left\{ \frac{1}{\sigma} B \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} w^{\alpha_m (1-\sigma)} \psi_m^{\sigma-1} \right\}$ captures all the terms not associated with the cost of an input bundle for the final good.[13] [14] Importer m will choose the supplier $x_{j,t}$ that gives the highest input-specific profits. Since the decision of input j is wholly separate from the decision of other inputs, I now focus attention only on the market for one input and drop the j subscript.

How does an importer decide which exporter maximizes profits? It is a maximization problem of discrete choice, so expected profits are calculated for each choice, and the partner with the highest expected profits will be chosen. Dividing Equation (1.5) through by $(\sigma - 1)$, I define the *exporter-specific* expected log profit term for any choice x_t^m as $\overline{\pi}_t^m (x_t^m, \boldsymbol{\beta})$:

$$\overline{\pi}_t^m (x_t^m, \boldsymbol{\beta}) = \xi \ln \lambda_{x,t} + \beta_p \mathbb{E}\left[\ln p_{x,t}^m\right] - \beta_x \mathbb{1}\{x_t^m \neq x_{t-1}^m\} - \beta_c \mathbb{1}\{c_t^m \neq c_{t-1}^m\} \quad (1.6)$$

where $\xi = \nu$, $\beta_p = -(1-\alpha)\gamma$, $\beta_x = (1-\alpha)\gamma\zeta_x$, and $\beta_c = (1-\alpha)\gamma\zeta_c$. I summarize the vector of unknown parameters as $\boldsymbol{\beta} = \{\beta_p, \beta_x, \beta_c, \xi\}$.

Equation (1.6) is the cornerstone of my estimation strategy. Starting from a

[13]In Equation (1.5), I use Jensen's Inequality and the fact that the expected price is almost-surely constant to assert that the log of the expected price is equal to the expected log price.

[14]Intuitively, for elasticities of substitution $\sigma > 1$, higher quality $\lambda_{x,j,t}$ leads to higher profits, while higher prices lead to lower profits.

general model of importing behavior, I have derived a choice-specific profit equation that can be estimated using techniques of structural industrial organization[15]. To summarize this equation in words, if importer m chooses a different exporter than they used in the previous period, then this firm must they must pay a fixed cost β_x, while if they use a different exporter in a different city, they pay $\beta_x + \beta_c$. The parameter β_p is a measure of how sensitive switching is to changes in price. Estimating $\{\beta_p, \beta_x, \beta_c\}$ by industry will provide a measure of the frictions firms face in switching partners and locations, and enable the posing of counterfactual experiments.

Estimating the unknowns in Equation (1.6) can be achieved by calculating expected log profits from each exporter, using observed outcome data to find the most likely values. Given the previous period state variables $\{x_{t-1}, p_{t-1}\}$, it is possible to rank an importer's expected profits from choosing any exporter x_t. The observed exporter choice in the data should be the one such that expected profits from that exporter are higher than all other potential choices. As in Rust (1987), I allow for a stochastic profit shock from choosing x_t that is observable to the importer, $\epsilon^m_{x,t}$, which helps the model match the data[16]. I use data on observed outcomes, prices, and estimated exporter quality to solve for the parameters via maximum likelihood estimation.

1.3.2 Prices

1.3.2.1 Exporters

Within any product category j there are numerous exporters x producing individual varieties. They set the price for their variety at time t based upon their firm-specific marginal cost, which in turn depends on their quality choice $\lambda_{x,t}$. I follow

[15]This equation resembles the worker utility function from choosing different employers discussed in Fox (2010).

[16]Appendix E lays out a version of Equation (1.6) that accounts for the possibility of serial correlation.

the same functional form for exporter quality as in Hallak and Sivadasan (2011), and continue to drop the j subscript. I assume monopolistic competition, fixed markups over marginal cost, and a random difference in prices across importers it serves $\rho_{x,t}^{m}$:

$$p_{x,t}^{m} = \mu MC_{x,t}\rho_{t}^{m} = \mu\frac{1}{z_x}\left(\lambda_{x,t}\right)^{\beta}\rho_{x,t}^{m} \tag{1.7}$$

where z is the idiosyncratic productivity of exporter x, and λ is quality. Exporters simply set a price and wait to be chosen by importers. This simple setup allows me to set up the expected price function importers use.

Taking logs, and assuming that the year-to-year changes in quality of an exporter is small over time, we obtain a transition rule for prices.

$$\ln p_{x,t}^{m} = \ln p_{x,t-1}^{m} + \left(\ln \rho_{x,t}^{m} - \ln \rho_{x,t-1}^{m}\right) \tag{1.8}$$

1.3.2.2 Price Evolution

In this section, I use Equation (1.8) to specify a simple one-step ahead process for prices, $f\left(p_{x,t}|p_{x,t-1}, x_{t-1}, x_t\right)$ that is known to importers. Thus I can specify every exporter price that an importer faces.

Importers know both what prices were paid by other firms in previous periods, and the distribution of shocks to those prices in the next period. Guided by Equation (1.8), the basic formula I apply is as follows: firms expect to pay the price they paid last period if they keep their partner, while they expect to pay the average price all other importers paid from a given supplier if they switch to that supplier. In addition, importers are aware that prices in a given geographic area will change by a given amount from one year to the next, and know that change perfectly.[17] However, there is also a stochastic element to the price with a known mean and standard

[17] In terms of Equation (1.8), one component of the $\left(\ln \rho_{x,t}^{m} - \ln \rho_{x,t-1}^{m}\right)$ is a known increase in average prices across the entire city. If Importer A chooses to stay with Supplier Z in city Q, they expect the price paid last period plus the increase in prices in city Q.

deviation.

If importer m stays with its current partner x in city c, the price process is:

$$p^m_{x,t} = p^m_{x,t-1} + \eta_{c,t} + u^m_{x,t}, \quad u^m_{x,t} \sim \mathcal{N}\left(0, \sigma^2_{x,t}\right) \tag{1.9}$$

Importing firms know there is a city-specific change in prices $\eta_{c,t}$, as well as the distibrution of an exporter-specific realization of a shock. The city-specific price shocks are correlated for firms in the same city, so there is a city component and an exporter-specific component.

If importer m decides to use a different partner $\widetilde{x}$, then the price process is:

$$p^m_{\widetilde{x},t} = \frac{1}{N}\sum_{n=1}^{N} p^n_{\widetilde{x},t-1} + \eta_{\widetilde{c},t} + u^m_{\widetilde{x},t} \quad u^m_{\widetilde{x},t} \sim \mathcal{N}\left(0, \sigma^2_{\widetilde{x},t}\right) \tag{1.10}$$

N is the number of firms who imported from firm $\widetilde{x}$ from the previous period, and they are indexed $n = 1, ...N$. Each price paid by importer n is $p^n_{\widetilde{x},t-1}$. As above, there is both a city shock to prices and an importer-specific realization of the exporter price shock.

Given the specification of these different prices based on shocks calibrated to data in period $t-1$ and t, I can write down a density function for prices $f\left(p_{x,t}|p_{x,t-1}, x_{t-1}, x_t\right)$. In other words, given state variables p and x, and future choice x', the price p' from that x' can be predicted by any importer. The parameters $\{\eta_{c,t}\}_{c=1}^{C}$ are the mean changes in price for any city, and are known by the importing firm. I assume the stochastic parameters $u^m_{x,t}$ are normally distributed with mean zero and standard deviations $\sigma_{x,t}$ (each exporter has a particular distribution of price shocks known to importers, but the specific value of which is observed only after the match occurs). I use the LFTTD data to calibrate the parameters $\{\{\eta_{c,t}\}_{c=1}^{C}, \{\sigma_{x,t}\}_{x=1}^{X}\}$ by using observed prices in both pre- and post-periods and estimating equations (1.9)-(1.10) for each industry[18].

1.3.3 Value Function

Individual importers make their choice of exporter based on price concerns, quality concerns and any added costs involved from changing their current exporter. Entering period t, importer m has two state variables that affect its choice, given by $\overline{\pi}_t^m \left(x_t^m, \boldsymbol{\beta}\right)$ in Equation (1.6): the exporter used last period, x_{t-1}^m with location c_{t-1}^m, and (in order to form price expectations) the price paid to that exporter $p_{x,t-1}^m$. Based on these state variables, knowledge about prices in other locations, and the costs of switching one's current exporter, the importing firm must choose which exporter to use in the current period, x_t. Upon making this choice, the state variables and profit shock $\epsilon_{x,t}^m$ evolve according to the joint density $h\left(p_{x,t}, \epsilon_t | p_{t-1}, x_{t-1}, x_t, \epsilon_{t-1}\right)$.

Infinitely-lived importer m chooses an exporter x in each period in order to maximize the present discounted stream of expected profits. With single-period expected profits described by Equation (1.6), the infinite-time problem for any importer (dropping the m superscript) is summarized by the following value function:

$$V\left(p_{t-1}, x_{t-1}, \epsilon_{x,t-1}\right) = \max_{\{x_t, x_{t+1}, \ldots\}} \mathbb{E}\left[\sum_{\tau=t}^{\infty} \delta^{\tau-t}\left(\overline{\pi}_\tau\left(x_\tau, p_{\tau-1}, x_{\tau-1}, \boldsymbol{\beta}\right) + \epsilon_{x,t}\right)\right] \tag{1.11}$$

where the expectation operator is taken over the possible evolution of (p_t, ϵ_t), governed by the density $h\left(p_t, \epsilon_t | p_{t-1}, x_{t-1}, x_t, \epsilon_{t-1}\right)$ at every period t. Recall that the price from choosing exporter x_t is not known before making the choice, but is predicted based on $p_{x,t-1}, x_{t-1}$ and x_t, according to the density function $f\left(p_{x,t} | p_{x,t-1}, x_{t-1}, x_t\right)$.

Writing the one-step ahead value of any variable a as a', the value function in

[18] If no prior year information is available for a potential supplier- i.e. an importer chooses a supplier that did not exist in the previous year- I allow the expected price to be the average price among all exporters in that city in the previous period. If there is no city information in the previous period, I drop that exporter. If an exporter is only found in the pre-period, then I calibrate $\{\eta_{c,t}, \sigma_{x,t}\}$ using all other firms and use them to form the expected price from using that exporter.

(1.11) can be rewritten as a Bellman Equation:

$$V\left(p,x,\epsilon\right)=\max_{x'}\quad\overline{\pi}\left(x',p,x,\boldsymbol{\beta}\right)+\epsilon_{x'}+\delta EV\left(x',p,x,\epsilon\right)$$

for

$$EV\left(x',p,x,\epsilon\right)=\int\limits_{p'}\int\limits_{\epsilon'}V\left(p',x',\epsilon'\right)h\left(p',\epsilon'|p,x,x',\epsilon\right)dp'd\epsilon'. \tag{1.12}$$

At this point, I make a key assumption about the joint density of the state variables and the profit shock: that they evolve separately from each other.

Assumption 1. (Conditional Independence) *The joint transition density of p_t and ϵ_t can be decomposed as:*

$$h\left(p_{t+1},\epsilon_{t+1}|p_t,x_t,x_{t+1},\epsilon_t\right)=g\left(\epsilon_{t+1}\right)f\left(p_{t+1}|p_t,x_t,x_{t+1}\right)$$

I also assume that the profit shock ϵ is distributed according to a multivariate extreme value distribution, with known parameters:

Assumption 2. *The profit shock is distributed Type I Extreme Value (Gumbel). The cumulative distribution function G is*

$$Pr\left(\epsilon_t<y\right)=G\left(y\right)=\exp\left\{-\exp\left\{-y-\gamma\right\}\right\}$$

for $\gamma=0.577...$ (Euler's constant).

These two assumptions permit the computation of choice probabilities for any particular outcome :

Proposition 1. *Let the value of a present time variable a one period ago be written as a_{-1}, and one period in the future be written as a'. Given Assumptions 1 and*

2, and grouping together the state variables as $s = \{p_{-1}, x_{-1}\}$*, the probability of observing a particular exporter choice* x^C *conditional on state* s *and cost parameters* $\boldsymbol{\beta}$*,* $P\left(x^C|s,\boldsymbol{\beta}\right)$*, is:*

$$P\left(x^C|s,\boldsymbol{\beta}\right) = \frac{\exp\left[\overline{\pi}\left(x^C, s, \boldsymbol{\beta}\right) + \delta EV\left(x^C, s\right)\right]}{\sum_{\widehat{x}\in X}\exp\left[\overline{\pi}\left(\widehat{x}, s, \boldsymbol{\beta}\right) + \delta EV\left(\widehat{x}, s\right)\right]} \tag{1.13}$$

where the function $EV(x,s)$ *is the solution to the fixed point problem:*

$$EV(x,s) = \int_{s'} \log\left\{\sum_{x'\in X}\exp\left[\overline{\pi}\left(x', s', \boldsymbol{\beta}\right) + \delta EV\left(x', s'\right)\right]\right\} f\left(s'|s,x\right) \tag{1.14}$$

Proof *See Appendix 1.C.*

1.3.4 Maximum Likelihood Estimation

The parameters $\boldsymbol{\beta}$ can then be found via maximum likelihood estimation. Let $x_{t-1}^m, p_{x,t-1}^m$ be the actual choices of exporter and price paid at time $t-1$ for importer m from data. Then the likelihood of observing importer m choosing exporter x_t^m is:

$$L\left(x_t^m|p_{x,t-1}^m, x_{t-1}^m, \boldsymbol{\beta}\right) = P\left(x_t^m|x_{t-1}^m, p_{x,t-1}^m, \boldsymbol{\beta}\right)\cdot f\left(p_{x,t}^m|p_{x,t-1}^m, x_{t-1}^m, x_t^m\right)$$

And thus the total likelihood function for the set of importer choices at time t is:

$$\mathcal{L}(\boldsymbol{\beta}) = \prod_{m=1}^{M} P\left(x_t^m|x_{t-1}^m, p_{t-1}^m, \boldsymbol{\beta}\right)\cdot f\left(p_{x,t}^m|p_{x,t-1}^m, x_{t-1}^m, x_t^m\right)$$

The constraints for the maximization problem are the system of fixed point equations defined by Equation (1.14). To solve this problem, I follow the MPEC approach as described in Su and Judd (2012) and Dubé, Fox, and Su (2012), namely an inner loop for solving the fixed point problem in (1.14) for the constraint vector $\mathbf{EV}$ and $\boldsymbol{\beta}$, and testing each candidate $\boldsymbol{\beta}$ within the likelihood function to see where the function is maximized. Thus the problem to solve is:

$$\max_{\boldsymbol{\beta}} \mathcal{L}(\boldsymbol{\beta}) =$$

$$\max_{\boldsymbol{\beta}} \sum_{m=1}^{M} \frac{\exp\left[\overline{\pi}_t^m \left(x_t^m, s_t^m, \boldsymbol{\beta}\right) + \delta EV\left(x_t^m, s_t^m\right)\right]}{\sum_{\widehat{x}_t^m \in X} \exp\left[\overline{\pi}_t^m \left(\widehat{x}_t^m, s_t^m, \boldsymbol{\beta}\right) + \delta EV\left(\widehat{x}_t^m, s_t^m\right)\right]} + \sum_{m=1}^{M} f\left(p_{x,t}^m | s_t^m, x_t^m\right) \quad (1.15)$$

$$s.t.$$

$$EV\left(x_t, s_t\right) = \int_{s_{t+1}} \log\left\{\sum_{x_{t+1} \in X} \exp\left[\overline{\pi}_{t+1}\left(x_{t+1}, s_{t+1}, \boldsymbol{\beta}\right) + \delta EV\left(x_{t+1}, s_{t+1}\right)\right]\right\} f\left(s_{t+1} | s_t, x_t\right) \quad (1.16)$$

Solving this problem produces maximum likelihood estimates for the vector of parameters $\boldsymbol{\beta}$. The next section describes the particulars of how this model is taken to the data.

1.4 Estimation

This section has three objectives: first, I describe the specific assumptions involved in discretizing the state space for the constrained maximization problem in Equations (1.15)-(1.16) and model performance on generated data with pre-set parameter values. Second, I specify the process used to calculate quality. Third, I present analysis of the raw structural parameters obtained from the solution of the constrained maximization problem using U.S.-China trade data.

1.4.1 Implementation

In order to estimate the above model, I need to solve the system of equations defined by (1.16) for the unknown elements EV and $\boldsymbol{\beta}$. To do this, I discretize the price state space into N intervals, allowing me to rewrite the fixed point equation (16) as:

$$EV\left(x_t, \widehat{s}_t\right) = \sum_{\widehat{s}_{t+1}=1}^{N} \log \left\{ \sum_{x_{t+1}\in X} \exp\left[\overline{\pi}_{t+1}\left(x_{t+1}, \widehat{s}_{t+1}, \boldsymbol{\beta}\right) + \delta EV\left(x_{t+1}, \widehat{s}_{t+1}\right)\right] \right\} Pr\left(\widehat{s}_{t+1} | \widehat{s}_t, x_t\right) \tag{1.17}$$

where $\widehat{p}$ is the midpoint of each price interval, chosen such that $\frac{1}{N}$ of all firms are in each interval. My use of MPEC in solving the maximum likelihood model follows the description from Su and Judd (2012) and Dubé, Fox, and Su (2012). The MPEC maximization protocol uses values of the vector $\boldsymbol{\beta}$ that satisfy the fixed point equation (1.15), given expected prices and price transition probabilities for each potential choice, and selects the vector that delivers the highest likelihood. As a simple example to fix ideas, suppose there are 30 exporters in an industry and N discrete price states. Then there are $30N$ possible state values and 30 possible choices, meaning that the vector $\mathbf{EV}$ contains $900N$ elements, one for each value of $EV\left(x_t, \widehat{s}_t\right)$. Thus the constraint set in (17) is a fixed point problem of $900N$ equations and $900N+4$ unknowns, where the additional 4 unknowns are $\boldsymbol{\beta} = \{\beta_p, \beta_x, \beta_c, \xi\}$. Each of the possible values of $\boldsymbol{\beta}$ and $\mathbf{EV}$ that satisfy these constraints are tested in the objective function (1.15) to see which give the closest match between the estimated probabilities and the true data.

Before computing the model on U.S.-China trade data, I first set the parameters at fixed values and create 250 Monte Carlo replications of data based on these values. Every importer m is assigned an exporter x_{t-1} and price $p_{x,t-1}$ from a previous period, and predicts the expected price received from every potential exporter x_t, i.e. $\mathbb{E}\left[p_{x,t}|p_{x,t-1}, x_{t-1}, x_t\right]$. The importer matches with an exporter, given both these expected prices and the pre-set values of the parameters β_p, β_x, and β_c.[19] I then utilize the observed outcomes and prices from each dataset to run the maximum likelihood problem found in (1.15) and (1.17), extracting the cost parameters consistent with those choices. I set $\delta = 0.975$ and use $N = 5$ price states.

Since the total number of importers (M), exporters (X), and exporter cities (C) are free to choose, I set the number of importers at 30 and create three different samples: one small ($M = 30, X = 4, C = 3$), one with the average number of exporters in the data but few cities ($X = 33, C = 3$), and one matching both the average number of exporters and the average number of cities in the data ($X = 33, C = 9$).[20] I then run the estimation routine on each set of data, and report summary statistics for how well the procedure matches the pre-set values. The results of this procedure are presented in Table 3.

It is clear that the estimation routine matches the pre-set parameters poorly on the very small sample. Furthermore, mean estimates of the exporter switching effect

[19]For this estimation, I do not include quality estimation terms, given the extra assumptions I would have to make to run the quality estimation protocol described below. The profit equation is the same as (3), only without the λ term.

[20]The average number of Chinese exporters in an HS6 industry is 33.58. The median number of exporters is eight. The industry at the 90th percentile of exporters contains 81 exporters. 15.3% of the 3000 or so HS6 codes found in the trade data contain only one exporter. These figures are based on computation of the "main" exporters, i.e. exporters who are found after assigning a "plurality exporter" to each importer.

β_x are extremely high. These results occur because with such a small sample space (four exporters and three cities), a number of Monte Carlo runs likely have very few cases of within-city switching, providing very high estimates for the base exporter switching cost. Yet even in this scenario, the median results preserve the ordering of the originally set parameters. In addition, the elasticity of the switching decision with respect to prices, β_p is of reasonable sign and size.

Once the sample size is extended to 33 exporters (the average number of exporters in an HS6 industry), some of the results improve. For Sample B, which contains fewer cities, we see a vast improvement in the measurement of the price coefficient β_p, and the exporter switching cost β_x. A greater number of exporter possibilities permits more partner switching observations, allowing for better estimation of this parameter. Notably, the mean and median of the outside-city switching cost β_c is much higher than the pre-set value of the parameter, as the number of cities is small enough to make the estimation procedure assign higher costs of switching cities.

Finally, results for Sample C demonstrate that the procedure improves further when the number of cities is increased to the average number of exporting cities found in the LFTTD, $C = 9$. Not only do estimates of the city switching cost decrease in mean and median to levels much closer to the preassigned values, but the exporter switching cost and price elasticity similarly approach their values. My estimation procedure thus is expected to perform better in industries that have enough observations of within-city, out-of-city, and non-switching observations to estimate the parameters of interest, and in those industries, will deliver reasonable results.

1.4.2 Data Preparation

In this section, I describe how I bring the LFTTD data to the model, in order to run the MLE problem of Equation (1.15) with the constraints in Equation (1.17). To do so, I must calculate the one-period log expected profits from an importer choosing each potential exporter x_t as given in Equation (1.6). There are four elements to this profit equation:

- Whether x_t is different from an importer's previous partner.
- Whether x_t is located in a different city from an importer's previous partner.
- The expected price of x_t.
- The quality of x_t.

The first two are easily identified using the MID variable discussed in Section 1.2. I described the process for calculating expected prices in Section 1.3.2. It remains to specify the process through which I estimate the quality of an exporter, λ. I consider exporter quality as an estimate of exporter heterogeneity given data in the LFTTD. The intuition follows from Kim and Petrin (2010) and Khandewal (2011): if exporters are very similar in terms of observables but one charges a higher price, then that one has a higher quality.

Specifically, I use the control function methodology of Kim and Petrin (2010) to account for unobserved supplier heterogeneity that is likely to be positively correlated with the price, via the following regression:

$$\ln p_{x,t} = \ln \mu - \log z_{x,t} + \ln \lambda_{x,t} \tag{1.18}$$

This equation follows directly from the specification of exporter prices described in Section 1.3.2.1, although the price is now the average price of exporter x_t charged to all importers and is not specific to an importer-exporter match.[21] From the trade data, I cannot observe the productivity of individual Chinese exporters. However, there are a number of variables in the data that I use to proxy for productivity, including total U.S. exports, number of HS products exported, number of years exporting to

[21] I also assume the exponent on quality β is 1.

the U.S., number of import partners, and number of transactions. For each industry, I group these terms into a firm-specific vector of covariates Z_x, and together with time fixed effects, regress the exporter's average offered price (firm-level unit value) on these variables. I then take the residual from this regression and call it quality. The approach is similar to the "quality ladder" estimation procedure described in Khandewal (2010).[22]

Finally, I describe the final pieces of the puzzle necessary to run the MLE problem above. Firstly, with some industry variation, some U.S. importers use multiple exporters each year. As before, rather than counting every possible permutation of exporters as a discrete choice, I restrict attention to that exporter from which a U.S. importer obtained the plurality (highest percentage) of its imports from each year. Thus the "choice" in the discrete choice model is which exporter the firm imports the most from, rather than which exporter the firm uses.[23]

A second simplification is to use HS6 categories: even though the trade data is measured at the most disaggregated level possible - HS10 - many measures of industrial characteristics that I use to compare my results with are only at the HS6 level. This is because the HS6 level is the most disaggregated level of product that is consistent for all countries. The simplification also gives more observations and more potential for wider geographic effects. At the same time, any switching behavior that goes on at a more disaggregated level is swamped by this aggregation, and the degree of product heterogeneity across firms is likely much larger than at the more disaggregated level.

Additionally, given the fact that not every exporter is found in both periods, I have to take a stand on the set of potential exporters X. I define the set of possible

[22] As a check, I estimate the model on goods that are considered highly homogeneous across sellers. The results from including quality and leaving out quality in these industries are qualitatively similar.

[23] Analysis of the LFTTD indicates that U.S. importers typically import a very large share of their total imports from only one partner. The average share of imports that come from a U.S. importer's main Chinese partner is 83.9%, with a standard deviation of 22%.

exporter choices broadly, consisting of a) any exporter used in time t and b) any new exporter in time $t+1$, as long as I know what price they charged in time t. As described above, I am making the exporter choice one of "where do I get my majority of imports from", meaning it is possible that we have some "new" exporters found in time $t+1$ that have price information from time t, even though they did not actually appear as any importer's majority supplier in time t.

The last step is to clean the LFTTD by eliminating unreasonable prices. Unit values in the LFTTD are particularly prone to wildly unreasonable outliers, sometimes caused by firms writing down a quantity of 1 instead of the standard quantity that should be used for a product, for example. Before averaging prices across transactions, I eliminate any transactions with prices greater than the 90th percentile for an HS6 industry that are also greater than 10 times the median price in that industry. I then repeat the process, again eliminating prices that are greater than 10 times the new median price.

I use the above procedure to estimate the model for a large number of industries, using data on U.S.-China trade from 2005-2006. I use TOMLAB / KNITRO to compute the Jacobian and the gradient for Equations (1.15) and (1.17) analytically, and then solve the above MLE problem.

1.4.3 Estimation Results

A key result from the estimation procedure is that the cost of switching is large. I run the model on 50 industries, chosen to represent industries across the spectrum of imported products from China that are also large enough to have both partner and city switching.[24] The value-weighted average of switching costs across the sample of industries is $\beta_x = 2.99$ and $\beta_c = 1.61$. The numeric results are interpreted in units of the Type I Extreme Value shock, which has mean 0 and standard deviation

[24] The list of industries and their trade shares are listed in Table 1.A.2.

$\sqrt{\frac{\pi^2}{6}} \approx 1.29$, which gives the following implication: for an importer to be indifferent between its current partner and some other potential partner in the same city charging the same price, the new partner must provide a positive shock to profits that is approximately $2.99/1.29 = 2.3$ standard deviations from the mean. If that new partner is located in a separate city, then that new partner must provide a positive shock to profits that is $(2.99 + 1.61)/1.29 = 3.6$ standard deviations from the mean. Thus the estimated parameters confirm the reduced form results that frictions from switching are large.

Furthermore, the costs are highly heterogeneous across industries. Rather than presenting the full battery of results (available upon request), in this subsection I present estimates of the parameters in illustrative industries.[25] These estimates are presented in Table 1.4.

I begin by presenting results for industries that have noteworthy spatial characteristics related to the location of exporters. The HS6 industries "Hand Pumps for Liquids" (HS6 841320) and "Files, rasps, and similar tools" (HS 820310) are both characterized by fairly low degrees of out-city switching. Of all switching importers in HS6 841320 from 2005 to 2006, only 30% switched cities. For HS6 820310, the respective figure is 15%. Thus the estimates should reflect the fact that switching cities is more costly through higher city-switching costs relative to partner-switching costs. On the other hand, the HS6 industries "Portable Digital ADP Machines" (HS6 847130) and "Motorcycles, Side-cars, Reciprocating Engine of a cylinder capacity greater than 50 cc but not exceeding 250 cc " (HS 871120) are characterized by very high levels of inter-city switching among switching firms: 72% find a partner in another city in HS 847130, while 86% switch cities in HS 871120. Thus the size of β_c relative to β_x should be much smaller than in the previous two industries, given that calculations of these parameters take into account how much switching is actually

[25] Not all industries discussed below are included in the sample of 50 industries above.

occurring. The first panel of Table 1.4 demonstrates this to be true: those industries with relative low levels of city switching have higher relative levels of city-switching costs, and the opposite for industries with greater city switching.

Another illustrative comparison is to examine the “slackness” of the market for imports- how many available exporters there are compared to the number of importers. Though most industries tend to have similar numbers of importers and exporters, the industry “Floor Coverings, Wall or Ceiling Coverings, of Polymers of Vinyl Chloride” (HS6 391810) has many more importers than available exporters: 58 to 42. Thus this is a market where importers are truly competing for exporters, a trend that should be reflected in low switching and high partner-switching costs. The middle panel of Table 1.4 demonstrates this to be true: the cost of switching exporters is a high proportion of the total exporter costs borne by switching both partner and city.

Next, I present selected results for textile imports from China, for the purpose of illustrating differences in elasticities of substitution. According to estimates for HS10 categories provided in Broda and Weinstein (2005), the industries “Gloves, Impregnable Plastic 4Chtt less than 50% Cotton, Man-Made Fibers, kt” (HS10 6116106500) and “Footwear, soles of rubber/plastic/leather, upper leather other protective toecap” (HS10 6403406000) have particularly high elasticities of substitution (between 9 and 15, where 20 is the generally accepted upper bound on feasibility of the estimate). The estimates are based on import data from the United States in the 1990s. High elasticities of substitution mean importers buying these products are very sensitive to changes in price, and are more likely to change their behavior in response to price changes. Although different elasticities of substitution are not included explicitly in the model, the characteristics of highly elastic industries should imply a high sensitivity to price changes, and indeed a strong response of switching, measured through β_p. On the other hand, industries such as “Men’s Underpants and Briefs of Manmade

Fibers, Knit" (HS10 6107110010) and "Ski/Snowmobile Gloves of Synthetic Fibers" (HS10 6116930800) are industries with particularly low elasticities of substition (between 1 and 2, where the non-inclusive lower bound from the estimation procedure is 1). In contrast to the industries described above, we would expect very weak responses of switching to price changes: these firms will not adjust their partners in response to price changes. The lower panel of Table 1.4 confirms these conclusions about switching and the elasticity of substitution: we see negative values for β_p in the industries earmarked as having very high substitution elasticicities, whereby an increase in price of one log point implies lower profits and thus, according to the model, a switch more likely. On the other hand, the high values of β_p imply that importers in those industries are not sensitive to price changes. This unresponsiveness shows that these firms are simply not likely to switch, as higher prices do not alter their choices.

I further make use of concordances developed by Brandt, Van Biesebroeck, Wang, and Zhang (2012) between HS codes and the China Industry Code (CIC) system to analyze different types of industries based on their domestic characteristics. Using China National Bureau of Statistics firm-level data for 2005, I isolate CIC industries where exporters have particular characteristics relevant to the importer-exporter partnership decision. For example, I compare industries with highly skilled workers to unskilled workers, and industries composed of large firms to industries composed of small firms. I then use the HS6-CIC concordances to estimate the switching behavior parameters among all firms importing in that CIC code. I summarize the estimates according to their underlying traits in Table 1.5.

The first set of results relates to the labor productivity of workers in different exporting industries. Chinese exporters in the industry "Arms and Ammunition" (CIC 3663) are in the lower tail of value added per worker relative to other industries. On the other hand, exporters in the industries "Rolling and Processing of Rare Earths" and “Tungsten and Molybdenum Smelting” have very high levels of value added per worker. As can be seen from the top panel of Table 5, industries with lower worker productivity tend to be characterized by lower exporter switching costs, while those industries with high levels of worker productivity have much higher exporter switching costs. This result is intuitive, as it implies importing firms who are importing products with highly productive workers receive greater relationship-specific benefits, and breaking up is more costly. On the other hand, firms with unproductive workers have little to distinguish themselves from competing firms, and thus have lower costs of switching from one to another.

I also compare results for firms of different employment sizes. Exporters in the industry “Other Ward Care and Medical Equipment” (CIC 3689) are of very small size, compared to exporters in the industry “Arms and Ammunition” (CIC 3663). The bottom panel shows importers importing in a product category that is dominated by small firms tend to value their relationship more, while an industry dominated by large firms is characterized by smaller exporter switching costs and more relationship breakups. This evidence suggests that smaller firms generally seem to be better tailored to specific needs of importing firms, which is in line with earlier findings in the literature, such as Blum et al (2010).

In summary, the results are broadly what we would expect of the estimates *ex ante*: higher exporter switching costs relative to city switching costs appear in industries with low levels of inter-city switching, many importers, and highly skilled workers. Lower exporter switching costs are found in industries with high levels of inter-city switching, and a high proportion of large firms. The next section uses the whole set of quantitative estimates to perform counterfactual experiments about the role of these frictions in import prices and trade flows.

1.5 Counterfactual Experiments

1.5.1 Changes in switching costs

Switching costs in this model can be interpreted as import market frictions, by which firms would like to import from particular other firms, but for some reason (lack of information, poor logistics, etc) do not actually import from these partners. There are potential efficiency gains to be realized if these costs were reduced, and importers could enjoy lower-priced alternatives rather than remaining "stuck" with their previous exporting partner. The structural model I estimated above allows me to assess how matching U.S. import prices from China, would change in response to falling switching costs. Conversely, I also examine how prices would be affected by increases in switching costs, such that switching occurred far less frequently than is seen in the data.

I follow the procedure outlined by the BLS Handbook of Methods to calculate the Import Price Index for my sample (U.S. Department of Labor, 2013).[26] Using the same sample of 50 industries as above, I then generate data according to a new set of parameters for each industry that reflect differences in switching costs. Keeping the state variables the same for each firm (supplier and price in the previous period), I generate outcomes given randomly drawn extreme-value shocks and the estimated parameters.

Specifically, for each industry j in the set of industries I use J, the industry price index P_j sums together firm-level prices, weighted by the share of one firm's imports

[26] I make one deviation from the BLS methodology, as I compute the index for each counterfactual and then compare, while the BLS measure compares individual prices first before aggregating to a comparative index. This is because I am comparing model simulations to other simulations. Results are qualitatively similar, but more subject to simulation outliers, if I compare each price first and make one index, rather than making two indices and then comparing.

in total industry imports:

$$P_j = \sum_{i \in I_j} \omega_i p_i \tag{1.19}$$

In the above, p_i is a summary measure-the mean or median- of firm i's received price across 1000 replications.[27] I weight each firm i by the value of its imports relative to total imports in that industry, ω_i. Given these industry level price ratios, I aggregate up using the share of industry imports in total trade w_j across the industries in my sample:

$$P = \sum_{j \in J} w_j P_j \tag{1.20}$$

The result is an price index that accounts for firm size and industry size. I create the same index for each different simulation and compare it to the generated data according to the original parameters.[28]The results are in Table 1.6.

The first thought experiment is to reduce both β_x (the partner-switching cost) and β_c (the city-switching cost) by half for all industries, and determine the size of the efficiency gain when more importers can separate and/or find better matches. I find that the U.S.-China Import Price Index decreases by 12.5% in response to such a change, as seen in Table 1.6 Column 2. Since the fixed switching cost is measured in units of the Type I Extreme Value ϵ shock, and the average β_x is approximately 3 (about 2.5 standard deviations of the shock), this can be thought of as a reduction in the size of the shock necessary to switch partners by about one standard deviation. Another way to think about this reduction is at the original parameter values (and

[27]Above, I used log prices to estimate the model. Since log price is potentially negative in certain industries, I exponentiate the price in each run of the generated data.

[28]In Appendix 1.D, I assess Model Fit by the same procedure, but comparing generated data from the originally estimated parameters to the true data

in the sample of industries I examine) approximately 57% of firms stayed with their partner. This reduction results in only about 18% of all total importers now staying with their partners. I calculate the price index for each of 1000 Monte Carlo simulations under both the original and the adjusted parameter set, and present the kernel densities in Figure 1.5.

One can see the same pattern in individual industries as well. Figure 1.6 shows the distribution of industry price indices (Equation 1.19) in separate HS codes with higher and lower switching costs. In many cases, the distribution is more skewed to the left, meaning prices are typically lower after allowing for more switching. However, there are also more cases of higher prices, such as in industry HS 610432, as a reduction in switching costs can also lead to worse matches. Importers in this industry tend to be insensitive to price in their final exporter decision, and thus an increase in switching often leads to higher prices than in the case with higher switching costs.

How to interpret such a decrease in switching costs? The Chinese government is well known for its investment in capital projects, especially infrastructure and its national development strategy focusing on inland provinces. One plausible scenario is that distribution networks to inland cities will improve greatly as China's economy further develops, exactly the type of advance that would lower the cost of adjusting import supply chains. A second is to think of these costs as information frictions, where importers are simply not aware of the alternative exporting options available to them. In this case, reduction in switching costs would be interpreted as the establishment of a registry where all exporters of a particular HS product would list their prices jointly, thus eliminating information frictions. A "gold standard" system where national governments ensure that producers are known and marketed together is another way to reduce switching costs. A third example would be better contracting institutions in China, allowing importers to adapt short-term contracts while still remaining confident in the ability to find quality inputs at acceptable prices over the long-term.

A second thought experiment is to weigh the relative effects of β_x vs. β_c. These parameters are broadly interpretable as the overall difficulty in leaving one's trading partner, for reasons of information frictions, long-term contracts, etc. versus city-specific effects, such as geographic agglomeration, better distribution networks, or how rapidly developing cities compare to well-known exporting hubs. Table 1.6 Column 3 shows then when the partner-switching cost β_x is reduced to zero, the amount of importers staying reduces even further, such that the total number of staying importers drops to 8%. Importers are also far more likely to switch city under this scenario, as the total cost of switching cities $\beta_x + \beta_c$ reduces substantially (β_x is typically 2 times higher than β_c in the average industry). The effects on prices are even stronger than the original case: if almost all importers can break up from their partners, then the new matches have a 15% lower Import Price Index, as compared to the original frictions. On the other hand, reducing the city friction to zero means that, as expected, importers do switch city more often, as can be seen in Table 1.6 Column 4. However, the partner friction is important enough to still leave 30% of all importers staying with their original partner, smaller than either of the previous two counterfactuals. The effects on prices is also smaller, with the Import Price Index reducing by 7.37%.

Finally, I consider the case where both the frictions are tripled, thus shutting down many of the original switches under the original parameters. Table 1.6 Column 5 demonstrates that such a change increases the number of importers staying with their partner to 90%, meaning the vast majority of firms are now unwilling to leave their partner. Indeed, the effect of importers being unable to move increases the prices received by 7.62%. Such a finding confirms the importance of supplier switching in overall price changes.

The results of these counterfactual experiments point more broadly to the importance of importer-exporter dynamics in considering the gains from trade over time. If, as is typically assumed in trade models, importers equally pay the lowest price available in a market, this presents the best scenario for welfare. Any buyer's divergence from the lowest price will necessarily lower estimates of the gains from trade. On the other hand, there are clear policy implications for importer efficiency from improving the general knowledge of the exporter base and helping importers have a better understanding of all possible options. Reducing information and contract frictions in practice can have a major impact on prices of goods, as the size of efficiency gains through lower prices are a robust prediction of the model I estimate, and are large in scope.

1.5.2 Potential for Re-Shoring

Many companies such as Apple have recently announced policies to move production of intermediate inputs back to the U.S. I use my model to estimate how low prices would have to be in order for importers from China to switch to another potential supplier to which different frictions apply. Specifically, I increase the size of the exporter choice set X by one firm, and assign it a different price to create separate scenarios. I eliminate the geographic switching cost that must be paid to switching this new firm, though it remains costly to switch from one's previous firm). I also assume this firm has the median "quality" (residual of the regression of price on observable exporter characteristics). I then re-solve the fixed point equation in (1.17) for each scenario, and see how many importers would choose to switch to this new firm over 1000 simulations. By using each firm's total share of imports in that industry, I can then determine what fraction of trade accrues to this new firm, i.e. how much trade would be "re-shored" given the existence of a firm with those prices and favorable switching costs. The experiment is one way of thinking about the existence of a highly favorable supplier located in the U.S., about which U.S. firms would tend to have much better information. The results are found in Table 1.7.

The results demonstrate the clear inertia involved in rousting importers from their Chinese partners, even with the elimination of geographic switching costs. If the hypothetical firm in each industry offered a price in the 75th percentile of the price distribution, only about 2% of trade value would come to this new U.S. firm. However, this price is already far lower than the average U.S. exporter price for firms in the same HS6 product. Furthermore, while it is possible to retrieve 3-4% of Chinese imports back to the U.S. by a hypothetical firm offering the mean or median price in each industry, this price is even farther away from the prevailing prices charged by U.S. exporters: a decrease of approximately 57% compared to U.S. exporters producing the same product. Thus efforts to return imports from the U.S. are significantly more difficult than simply offering a competitive price- the considerable benefits involved in maintaining existing relationships means that only a small share of imports would be able to move back to this hypothetical supplier.

1.6 Conclusion

In this paper, I have documented empirically and analytically that frictions from switching suppliers are large, and have important effects for import prices. U.S.-China importer-exporter relationships are characterized by a lack of turnover: 45% of importers remain with their supplier from one year to the next, and one-third of switchers switch within the same city. I estimate a model of dynamic discrete exporter choice, which uses partner switching costs and geographic switching costs in the context of U.S. decisions to import from Chinese exporters. I derive an exporter-specific profit function for importers from a heterogeneous firm model of international trade, and use the techniques of industrial organization to estimate the parameters of interest. Switching costs are large, and heterogeneous across industries. I then present a number of counterfactuals, including the effects on import prices from improved distribution channels and better information. Specifically, reducing switching costs such that U.S. importers can have better matches leads to 12.5% lower prices. Such a finding can be used to assess the effects of more complete partner information and lower distribution costs in an exporting country on welfare and aggregate productivity for the importing country. Indeed, this paper has shown that better partner options are often available for U.S. importers, but they are not always used. Increasing efficiency of matches will lead to higher gains from trade than are generally considered in models where price decisions occur at the country level, and presents a clear avenue for improving the productivity of U.S. firms through importing. The regional dimension of exporter choice decisions is also much stronger than has generally been known.

This project is merely the first step in a robust area for growth in the study of international trade transactions. The geographic link between importers and exporters gives us a new way to understand how shocks in a specific area move through international trade, a field of study that has thus far been limited to industry-to-industry linkages. Further research can augment this study that uses U.S.-China data and understand when importers change their country of importing, and where they go when they change. Switching costs across countries could play a role in explaining the slow response of exports to exchange rate shocks importers may be unable to quickly switch to more favorable import sources. In addition, future work will asses the impact of specific regional policies on importer behavior, such as the formation of special export zones in cities such as Shenzhen. Being able track exporter dropouts from the U.S. import data presents a reasonable degree of exogenous variation that can be used to determine U.S. final good producer behavior in response to an unexpected loss of members of its supply chain. Finally, the increasing availability of firm-level datasets puts the possibility of firm-to-firm linkages through trade transactions between the production data of separate countries closer to being realized, providing the most complete analysis of the micro-underpinnings of international trade.

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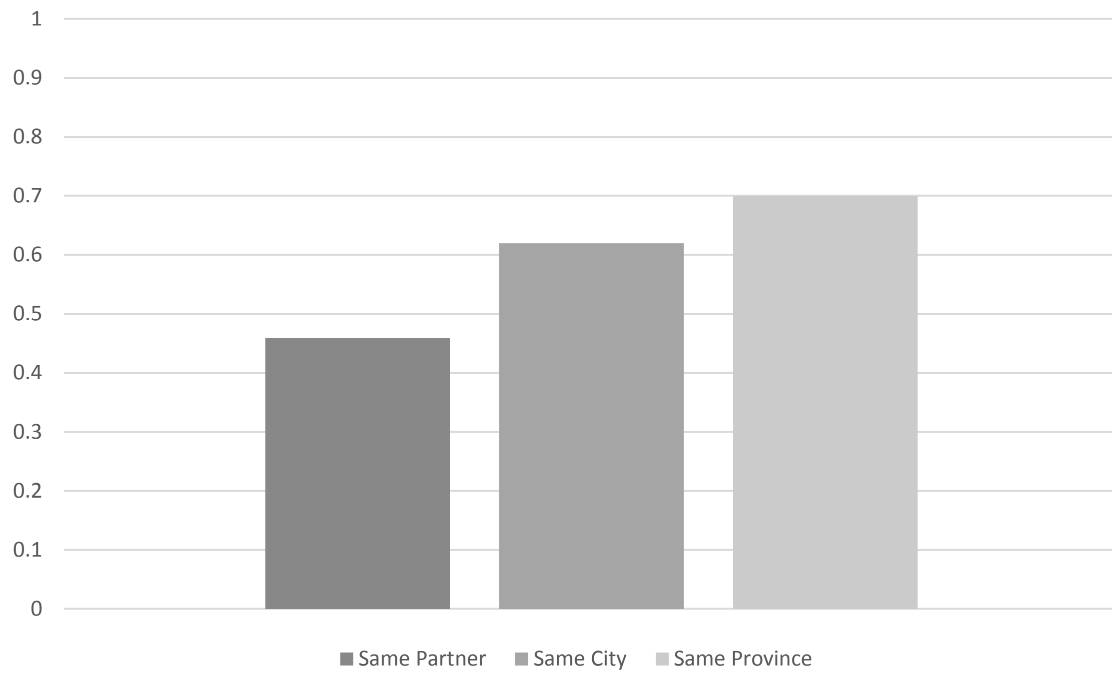
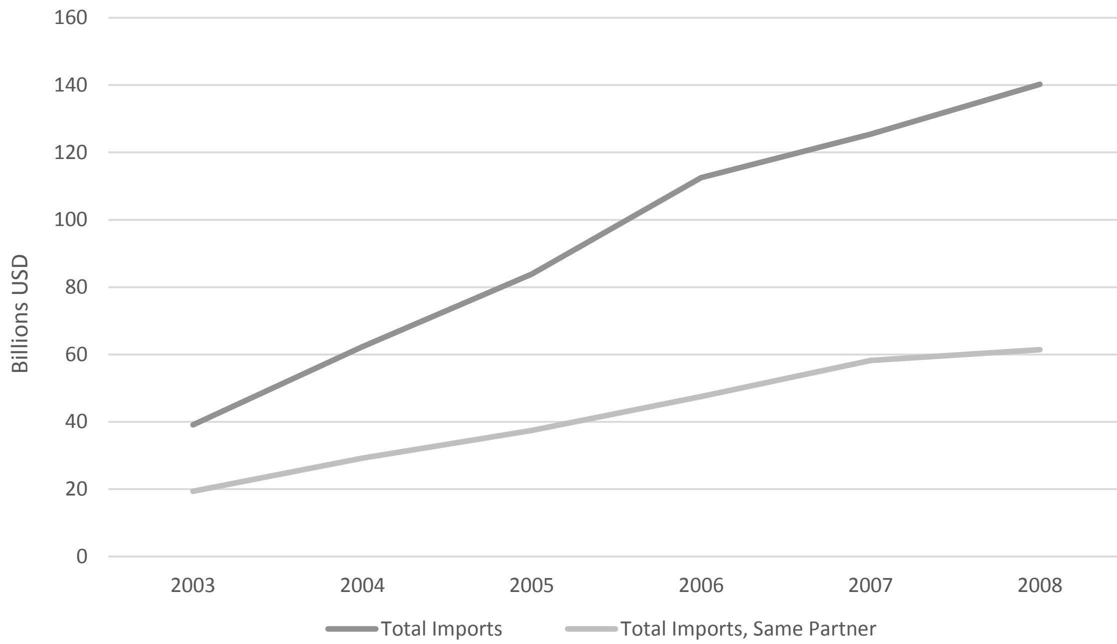
Figure 1.1: Year-to-Year "Staying" Percentages of U.S. Importers from China, 2003-8



Notes: To determine if a U.S. importer (firm + HS10 product) kept the same exporting partner from one year to the next, I calculate the majority partner for each importer in each year, using the value imported from each manufacturing ID in the Longitudinal Foreign Trade Transaction Database (LFTTD). If this majority partner remained the same from year-to-year, then the importer "stayed" with its partner. If the city of the majority partner remained the same, then the importer stayed in its city, and if the majority partner province remained the same, then the importer stayed in the same province. I apply the panel concordance for HS10 products developed by Pierce and Schott (2012).

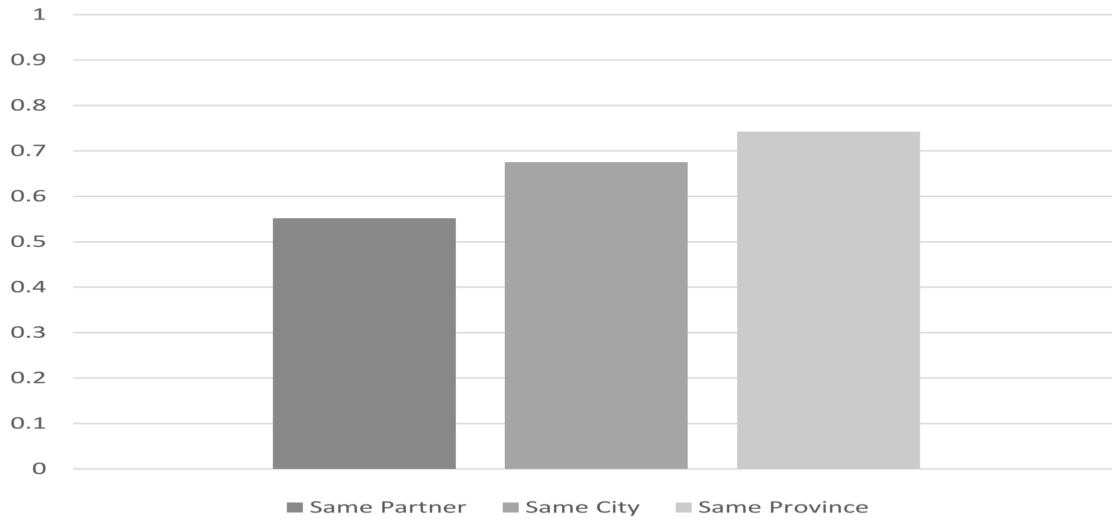
Figure 1.2: U.S. Total and “Same Partner” Imports from China, 2003-2008



Notes: Total U.S. imports from China comes is the sum of all arm’s length import value from the Longitudinal Foreign Trade Transaction Database (LFTTD). To determine if a U.S. importer (firm + HS10 product) kept the same exporting partner from one year to the next, I calculate the majority partner for each importer in each year. If this majority partner remained the same from year-to-year, then the importer “stayed” with its partner. Total imports among “Stayers” is the sum of all arm’s length import value from these importers. I apply the panel concordance for HS10 products developed by Pierce and Schott (2012). Note that “total imports” also includes importers who began importing the year in question (the “extensive margin”) while total imports from “stayers”, by definition, cannot. Imports from non-entrants (the “intensive margin”) are typically 85-90% of total imports from China over this time period.

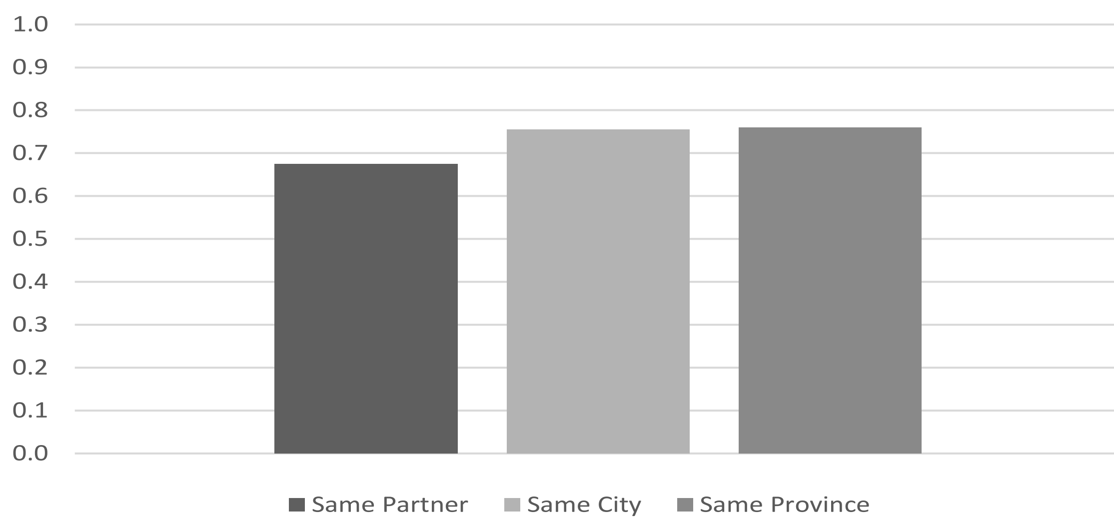
Figure 1.3: Percent of U.S. Importers from China "Staying", Additional Tests

Panel A: Year-to-Year "Staying" Percentages, Surviving Exporters, 2003-2008



Notes: For this figure, an importer is considered to have switched (not stayed with) its exporter only if two conditions are met: (a) the majority partner changed from one year to the next, and (b) the majority partner in the original year is still found exporting to someone else. The same procedure as above is followed to determine whether an importer stayed with its partner, city, or province.

Panel B: Year-to-Year "Staying" Percentages of U.S. Firms, 2003



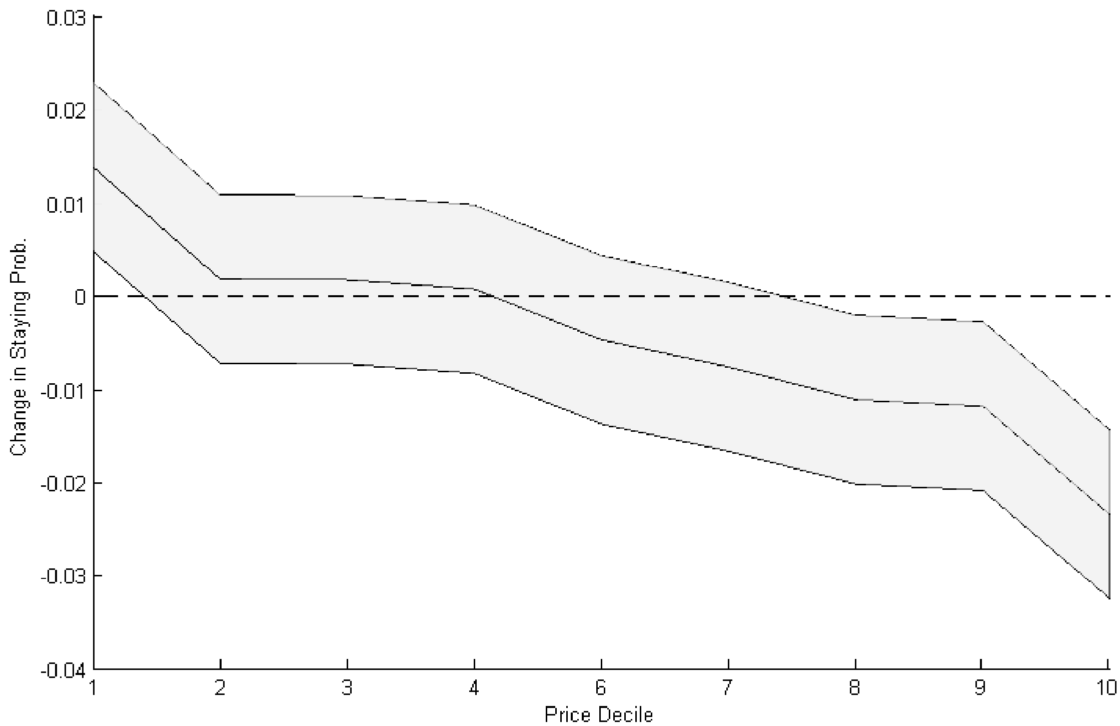
Notes: For this figure, an importer is considered to have switched from its exporter if it kept any one of its partners in any one of its HS10 imported products. The same procedure as above is followed to determine whether an importer stayed with its partner, city, or province.

Table 1.1: Determinants of Supplier Stay/Switch Decision

Dependent Variable: Stayed with Chinese Exporter Year-to-Year, 2002-2008				
	(1)	(2)	(3)	(4)
Log Price				
1st Decile	-0.0085**	0.0171***	0.0143***	0.0138***
	(0.004)	(0.003)	(0.003)	(0.003)
2nd Decile	-0.0052	0.0026	0.0020	0.0018
	(0.003)	(0.003)	(0.003)	(0.003)
3rd Decile	-0.0015	0.0015	0.0015	0.0017
	(0.003)	(0.003)	(0.003)	(0.003)
4th Decile	0.0005	0.0008	0.0007	0.0007
	(0.003)	(0.003)	(0.003)	(0.003)
6th Decile	-0.0038	-0.0043	-0.0046	-0.0047
	(0.003)	(0.003)	(0.003)	(0.003)
7th Decile	-0.0064**	-0.0069**	-0.0073**	-0.0076**
	(0.003)	(0.003)	(0.003)	(0.003)
8th Decile	-0.0109***	-0.0097***	-0.0110***	-0.0111***
	(0.003)	(0.003)	(0.003)	(0.003)
9th Decile	-0.0138***	-0.0091***	-0.0112***	-0.0118***
	(0.003)	(0.003)	(0.003)	(0.003)
10th Decile	-0.0357***	-0.0189***	-0.0225***	-0.0234***
	(0.003)	(0.003)	(0.003)	(0.003)
Log Supplier Size		0.0400***	0.0643***	0.0643***
		(0.001)	(0.001)	(0.001)
Supplier Age		-0.0017***	-0.0031***	-0.0029***
		(0.000)	(0.000)	(0.000)
Importer Size			-0.0322***	-0.0306***
			(0.001)	(0.001)
Constant	0.4438***	0.0211***	0.1047***	0.0863***
	(0.003)	(0.007)	(0.008)	(0.008)
Entry Year FE	No	No	No	Yes
N	510,485	510,485	510,485	510,485
R^2	0.07	0.09	0.09	0.10

Notes: Robust standard errors clustered at the HS10 level in brackets. *** significant at the 1% level, ** significant at the 5% level. HS10 and year fixed effects are included. The sample is the universe of U.S. importers (HS10 product code and fim combination) from China who are found two years in a row. The dependent variable is equal to 1 if the U.S. importer had the largest (plurality) share of its total import value from the same Chinese supplier in both years, and equal to 0 if not. Log price is the log average unit value across transactions with its majority partner in the previous year, standardized across products by subtracting the HS10 mean and dividing by the standard deviation. Supplier size is the total estimated exports of a Chinese supplier in the HS10 product code in the prior year, based on cross-section summation of total exports to the U.S. Supplier Age is calculated using the first year the Chinese supplier appears in the U.S. customs data, and subtracting it from the prior year. Importer size is the total size of imports in that HS10 product code in the prior year for any U.S. firm. Importer Entry Year is the first year a U.S. importers is found importing from China. Any importer that has the same share of imports from two separate Chinese suppliers is dropped.

Figure 1.4: Role of Price in Supplier Stay/Switch Decision



Notes: Log price is the log average unit value across transactions with its majority partner in the previous year, standardized across products by subtracting the HS10 mean and dividing by the standard deviation. This variable is split into deciles, and used as an independent variable in a linear probability model of importer staying status. The outer lines are a 99% confidence interval, calculated with robust standard errors clustered at the HS10 level. The sample is the universe of U.S. importers (HS10 product code and fim combination) from China who are found two years in a row over the years 2002-2008. Any importer that has the same share of imports from two separate Chinese suppliers is dropped. HS10 and year fixed effects are included. The fifth decile of price is excluded.

Table 1.2: Determinants of Supplier Stay/Switch Decision, Linear Price

Dependent Variable: Stayed with Chinese Exporter Year-to-Year, 2002-2008

	(1)	(2)	(3)	(4)
Log Price	-0.0084***	-0.0099***	-0.0104***	-0.0106***
	(0.001)	(0.001)	(0.001)	(0.001)
Log Supplier Size		0.0399***	0.0643***	0.0643***
		(0.001)	(0.001)	(0.001)
Supplier Age		-0.0024***	-0.0031***	-0.0029***
		(0.000)	(0.000)	(0.000)
Importer Size			-0.0322***	-0.0306***
			(0.001)	(0.001)
Constant	0.4353***	0.0193***	0.1011***	0.0823***
	(0.003)	(0.007)	(0.007)	(0.007)
Entry Year FE	No	No	No	Yes
N	510,485	510,485	510,485	510,485
R^2	0.07	0.09	0.10	0.10

Notes: Robust standard errors clustered at the HS10 level in brackets. *** significant at the 1% level, ** significant at the 5% level. HS10 and year fixed effects are included. The sample is the universe of U.S. importers (HS10 product code and fim combination) from China who are found two years in a row. The dependent variable is equal to 1 if the U.S. importer had the largest (plurality) share of its total import value from the same Chinese supplier in both years, and equal to 0 if not. Log price is the log average unit value across transactions with its majority partner in the previous year, standardized across products by subtracting the HS10 mean and dividing by the standard deviation. Supplier size is the total estimated exports of a Chinese supplier in the HS10 product code in the prior year, based on cross-section summation of total exports to the U.S. Supplier Age is calculated using the first year the Chinese supplier appears in the U.S. customs data, and subtracting it from the prior year. Importer size is the total size of imports in that HS10 product code in the prior year for any U.S. firm. Importer Entry Year is the first year a U.S. importers is found importing from China. Any importer that has the same share of imports from two separate Chinese suppliers is dropped.

Table 1.3: Monte Carlo Replication Results, based on 250 Replications

	β_p	β_x	β_c
Pre-Set Values	-0.5	-1	-3
Sample A: $M = 30, X = 4, C = 3$			
Mean	-0.626	1.269	4.728
Median	-0.564	0.954	3.690
Sample B: $M = 30, X = 33, C = 3$			
Mean	-0.543	0.843	8.209
Median	-0.540	0.837	5.017
Sample C: $M = 30, X = 33, C = 9$			
Mean	-0.538	0.985	3.427
Median	-0.512	1.055	3.081

Table 1.4: Selected Quantitative Estimates, HS Industrial Classification

HS6 Industry	β_p	β_x	β_c	β_c/β_x
Geographic Characteristics				
Low City Switching				
Hand Pumps for Liquids	0.08	1.67	3.95	2.36
Files, rasps, and similar tools	−0.06	2.74	2.95	1.08
High City Switching				
Portable Digital ADP Machines (Laptops)	−0.22	3.00	0.43	0.14
Motorcycles, Side-Cars, Engine $\geq$ 50 cc, $<$ 250 cc	−0.13	3.91	0.19	0.05
Market Size Characteristics				
Many more Importers than Exporters				
Floor Coverings, Wall or Ceiling Coverings, of Polymers of Vinyl Chloride	0.08	3.69	1.38	0.37
Pencils and Crayons	−0.04	3.47	1.21	0.35
Substitutability of Product				
High Elasticity of Substitution				
Men's Underpants and Briefs of Manmnade Fibers, Knit	−0.06	3.56	0.97	0.27
Ski/Snowmobile Gloves of Synthetic Fibers, Knit	−0.05	2.82	0.69	0.24
Low Elasticity of Substitution				
Gloves, Impregnable Plastic, 4 chtt, less than 50% cotton, manmade fiber, kt	0.51	1.45	1.64	1.13
Footwear, sole Rubber/Plastic/Leather, Upper Leather Protective Toe-Cap	0.25	2.76	1.75	0.63

Table 1.5: Selected Quantitative Estimates, China Industry Code (CIC) Industrial Classification

CIC Industry	β_p	β_x	β_c	β_c/β_x
Worker Characteristics				
Low Skilled Workers				
Arms and Ammunition	−0.03	1.67	2.66	1.58
High Skilled Workers				
Rolling and Processing of Rare Earths	−0.01	2.63	1.86	0.70
Tungsten and Molybdenum Smelting	0.04	2.64	1.73	0.71
Firm Size Characteristics				
Large Firms				
Arms and Ammunition	−0.03	1.67	2.66	1.58
Small Firms				
Other Medical and Ward Care Equipment	−0.00	2.98	1.30	0.44

Table 1.6: Counterfactual Results (I)

	Original Sample	$\beta_x \downarrow 50\%$ $\beta_c \downarrow 50\%$	$\beta_x \downarrow 100\%$ $\beta_c =$	$\beta_x =$ $\beta_c \downarrow 100\%$	$\beta_x \uparrow 200\%$ $\beta_c \uparrow 200\%$
Price Index	-	-12.50%	-15.20%	-7.37%	+7.62%
Staying	*57%*	18%	8%	31%	90%
City Staying	*75%*	43%	47%	46%	93%

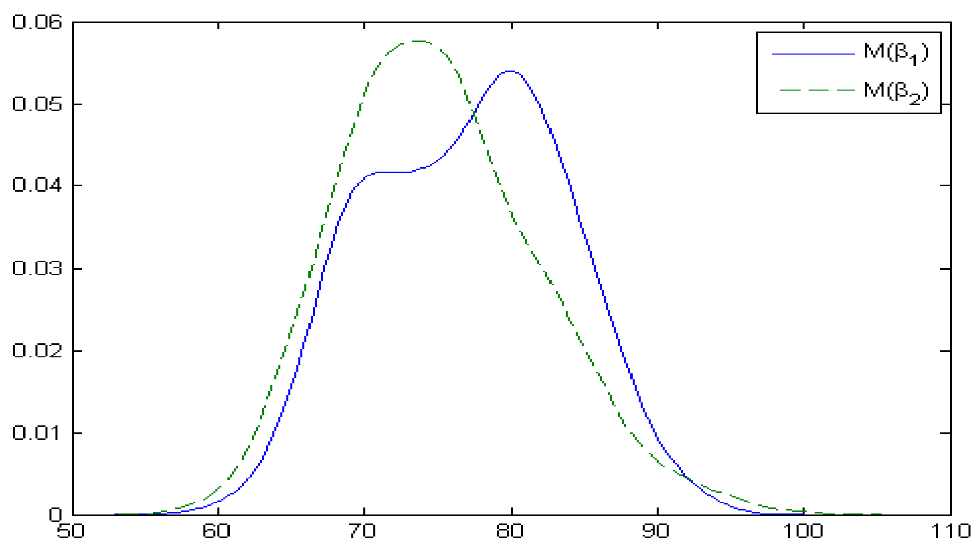
Notes: Objects computed by the model simulated with the originally estimated parameters are compared to the same objects in each of four counterfactual experiments: partner cost and city cost each reduced by half; partner cost reduced to zero, city cost unchanged; partner cost unchanged, city cost reduced to zero; and partner cost and city cost increased by three times. To compute the Price Index, I take the median received price across 1000 simulations for each importer, then weight each importer by its size within the industry. I then apply industry weights based on total trade among along simulated industries. The staying and city staying percentages are also estimated under the new parameter estimates.

Table 1.7: Counterfactual Results (II)

Price	Mean Sim. Trade Share	Median Sim. Trade Share	Reduction from U.S. Exp. Price
Median	3.86%	1.75%	56.27%
Mean	3.76%	1.53%	47.47%
75th Pct.	3.18%	0.77%	34.04%

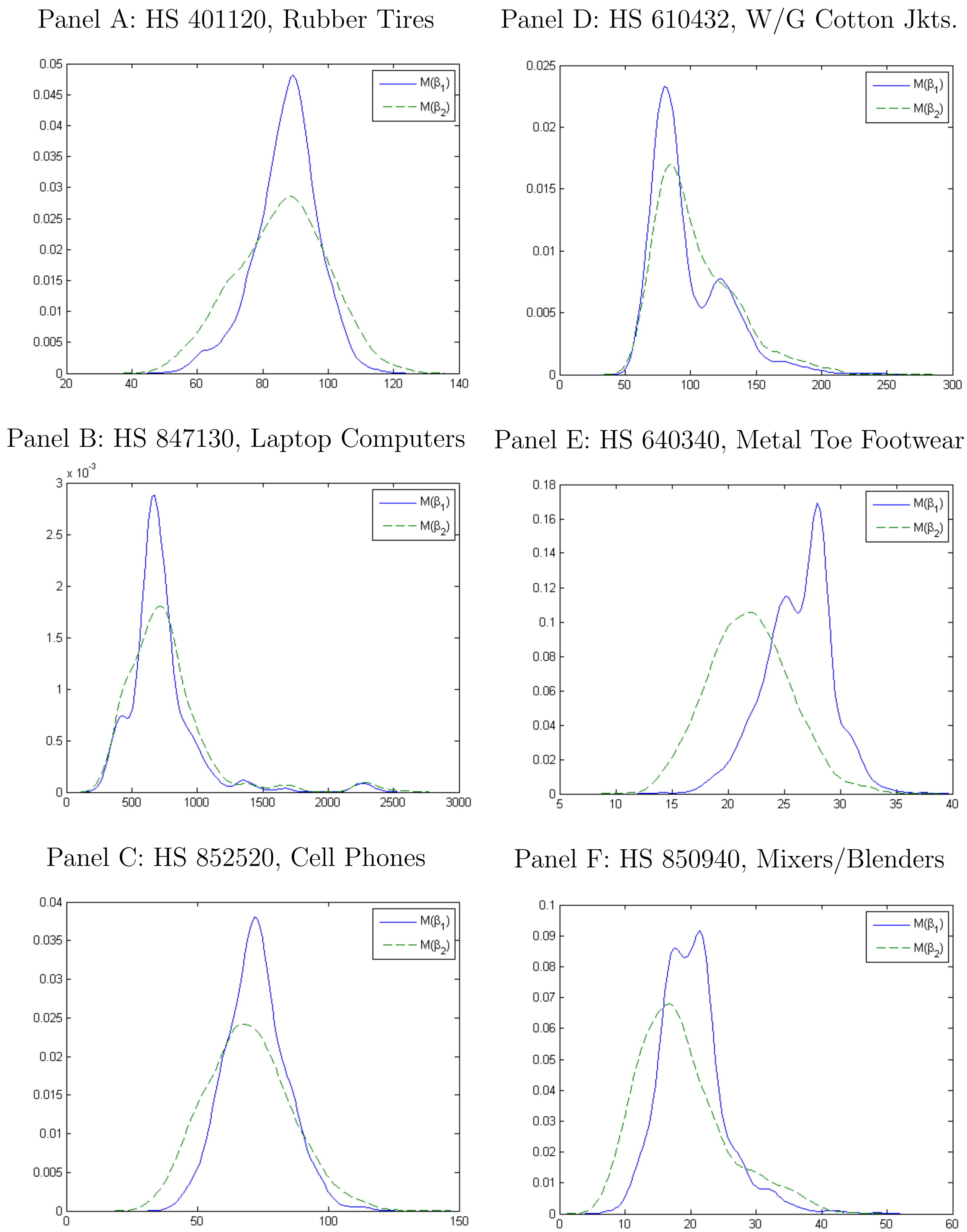
Notes: This table describes the flow of trade that would go to a hypothetical supplier not subject to geographic switching costs. The first column describes the size of the price charged by this hypothetical supplier compared to alternative Chinese suppliers. The second and third columns describe the percent of imports that would flow to this supplier, while the fourth column compares the price charged to the prevailing price charged by U.S. exporters for the same product.

Figure 1.5: Kernel Density Plots, Original $\boldsymbol{\beta}$ vs. Divided by Half



Notes: This figure presents kernel densities for the weighted average Import Price Index for importer-exporter matches predicted under the original parameters (solid line) and reducing switching costs by half (dashed line). I run 1000 replications of the model under each parameter set, and calculate the price index for the matches predicted in each replication.

Figure 1.6: Kernel Density Plots, Original $\boldsymbol{\beta}$ vs. Divided by Half, Selected Industries



Notes: This figure is kernel densities for the Industry Import Price Index for importer-exporter matches predicted under the original parameters (solid line) and reducing switching costs by half (dashed line), for individual industries. I run 1000 replications of the model under each parameter set, and calculate the price index for the matches predicted in each replication.

CHAPTER II

Gains from Offshoring? Evidence from U.S. Microdata

(Joint Work with Jooyoun Park and Jagadeesh Sivadasan)

2.1 Introduction

The impact of trade on the U.S. labor markets, particularly its contribution to the steep decline in manufacturing employment and increase in income inequality, has been a topic of intense academic and policy interest (Feenstra 2010, Krugman 2008, Autor, Dorn and Hanson 2012, Pierce and Schott 2013).[1] A major pathway through which trade can impact employment and wages is through the offshoring of production (Feenstra 2010, Blinder 2009).

However, empirical work has been significantly hampered by the lack of good quality data on offshoring (Kirkegaard, 2007). In this paper, we assemble a new dataset of offshoring events and firm performance, by linking offshoring-induced employment layoff events available from the Trade Adjustment Assistance (TAA) program to U.S. Census Bureau panel microdata. We use this linked dataset to evaluate the effects of

[1] Absolute employment levels in manufacturing have sharply declined over the last decade. Per BLS figures (data.bls.gov), manufacturing employment stayed relatively stable around 17 million from 1990 until about 2000, and then declined sharply to about 14 million by 2004, and then further to about 12 million in 2012.

offshoring on the remaining domestic activities of offshoring firms.

While media discourse about offshoring focuses largely on immediate job destruction at affected plants, theoretical predictions of the effects of offshoring vary across models. When the offshored activity has vertical linkages to the remaining domestic activities, there is potential for complementarities between offshoring and domestic activity (Harrison and McMillan 2011, Desai, Foley and Hines 2009, Sethupathy 2011). For example, in an extension of Grossman and Rossi-Hansberg's (2008) model of offshoring, Sethupathy (2011) finds that remaining domestic units benefit from lower input costs of the offshored input/task. While the net effect on employment is ambiguous, total output and profits at an offshoring firm go up; if workers share in the profits through bargaining, worker wages can be expected to rise at offshoring firms (and fall at non-offshoring firms who lose market share). Measured productivity at the domestic firm level is expected to go up as a result of lower costs for offshored tasks. Further, restructuring through offshoring may help firms avoid failure relative to non-offshorers (Park 2012a).[2]

However, if offshoring consists of unrelated "horizontal" activity (H-FDI), foreign employment may be a substitute for domestic employment, even in remaining domestic units, as support activities in other parts of the firm may be eliminated following offshoring (Harrison and McMillan 2011, Markusen and Maskus 2001). Further, with H-FDI, there is no linkage to other parts of the firm via lower input costs, so measured productivity at the (domestic) firm level may be unaffected. Thus the extent to which offshoring affects firm-level employment and other outcomes is an interesting empirical question.

The TAA program administered by the U.S. Department of Labor (USDOL) is

[2] Park (2012a) analyzes the theoretical employment effect of offshoring in a heterogeneous firm framework and finds the majority of industry-level negative effects stem from the "cleansing effect" - job destruction from the downsizing or death of non-offshoring firms that lose price competitiveness against their offshoring rivals. Our focus in this paper is not on the aggregate effects of offshoring, but rather on firm level outcomes for offshorers (which we assess by comparing offshorers to industry peers).

intended to help find reemployment for workers who lose jobs specifically because of trade related reasons. When layoffs occur at a plant, different concerned parties can file a petition with the USDOL; in our data 50% of petitions were filed by the company, 42% by the union, and the remaining 8% by state workforce offices. These petitions are then investigated by the USDOL to verify that layoffs were indeed trade-related. The rejection rate is non-trivial – in our sample about 45% of the petitions were rejected. Starting in 1999, approved petitions were classified into four categories based the reason for layoff, two of which (certified due to production relocation, or company's choice to replace the domestic tasks with imports) relate specifically to offshoring (the other two categories relate to import competition). More details about the TAA program and the petition data are provided in Appendix 2.A.

We use name-matching algorithms supplemented by extensive manual checks and modifications to link the names (and state) of establishments in the TAA petition data to the U.S. Census Bureau's business register (more details are provided in the Data Appendix). We achieve a match rate of about 70 percent; after cleaning and linking to the underlying Census micro data sets, and focusing only on initial offshoring events within firms our analysis covers about 1,400 unique offshoring firms with a limited set of variables (from the Longitudinal Business Database) and about 1,000 unique offshoring firms with greater information (from the Census and Annual Survey of Manufactures). We use these data to understand offshorers and examine the effects of offshoring on a range of outcomes at the (domestic) aggregate firm level.

First, we examine the basic characteristics of offshoring firms relative to the overall population of firms. Consistent with models where offshoring involves a fixed cost (e.g. Sethupathy 2011), we find that prior to initiation of offshoring, offshorers are larger, more capital intensive, and more productive than non-offshorers. Interestingly, offshoring firms were *not* more skill intensive than others in the industry.[3]

[3]Because large firms are typically more skill-intensive than smaller firms, relative to similar sized peers, offshorers appear to have lower skill-intensity. This consistent with economic theory, as we

Next, we examine the effects of offshoring. A key concern for this analysis in our setting is the potential endogeneity of the offshoring decision. We attempt to address this concern in a number of ways. Because the key drivers of the offshoring decision are likely to be industry shocks (e.g., reduction of transport costs, or increased competition from imports), in our baseline analysis, for each offshoring firm, we select two "controls" closest in size to an offshorer firm from within the same 3-digit industry, and form cells consisting of the offshorer and matched peers. The matching on size addresses potential concern that the effect of industry shocks varies by firm size. We then estimate difference-in-differences effects of offshoring, by comparing offshorers to the matched controls. In our most conservative specification, we include cell-year controls, that allow for differential shocks affecting each of the matched groups, so that the estimated effects are net of industry-size cell-year shocks.

We find that firms experience a significant decline in employment coincident with the initiation of offshoring, with the decline continuing for 3 to 4 years after. We find no evidence of firm employment recovery: over a six-year window of time from the initiation of offshoring, firm-level employment remains well below the pre-offshoring levels, with an average drop of 32% employment. Importantly, this pattern of employment reduction is very similar if we restrict the sample to multi-unit firms only, or to only non-offshoring plants within a offshoring firm. The magnitudes of declines in employment are similar for the aggregate of non-offshoring plants, suggesting significant declines in supporting activities at other parts of the firm. Consistent with the decline in employment, we find stark declines in output (28%) and capital (22%) at the firm level; again similar patterns also hold for the aggregate of non-affected plants within offshoring firms.

We find no discernible change in wages for either production workers or non-

may expect low skill activities to be precisely the ones to be offshored (e.g., Krugman 2008). But it provides a noteworthy contrast to the stylized facts for exporters, who are both larger as well as more skill-intensive than non-exporters (e.g., Bernard and Jensen 1999).

production workers. We find small gains in labor productivity (measured as real output per worker or real value added per worker). However, these gains appear to be achieved through more intense use of capital (as capital declines less than employment); firm level total factor productivity (TFP) measures that account for capital show no significant change relative to controls. We also examine firm survival rates, and find that the survival rate of firms who offshore is very similar to control group firms.

One potential source of bias for DID analysis is the presence of pre-existing trends. We specifically test for this in two ways. First, we plot the trends for both the treatment and control groups for a 13-year window around the offshoring event (see e.g. Figure **??**) as suggested by Angrist and Pischke (2009, who cite Autor 2003). These figures show that: (a) the offshoring firms do not show a significant declining trend in any of the key outcome variables prior to offshoring; (b) the trends for the control group of industry-employment matched firms are very similar prior to the offshoring event; and (c) there is a stark break in trend for offshorers relative to non-offshorers, consistent with changes being triggered by offshoring. Second, in the regression analysis, we include a test for pre-existing trends, and we confirm that the post-offshoring decline for employment, output and capital very significantly exceed the magnitude of preexisting trend effects (if any).

While our baseline DID analysis controls for endogeneity from omitted industry-size variables, there could be concerns about differential trends based on other (non-size) initial characteristics. To condition on a richer set of variables, we adopt a propensity score matching approach (Rosenbaum and Rubin 1985). In addition to employment, we include capital intensity as well as production and non-production wages in the propensity model. We then redo our analysis using controls matched on the propensity score, and we find our baseline results very robust to this alternative DID approach.

We undertake a number of additional checks of our results. First, one possibility not captured in our baseline analysis using manufacturing sector data is that potential benefits from offshoring are transmitted mainly to non-manufacturing activities of the firm. For example, if the offshored product is distributed by domestic retail or wholesale establishments, employment gains may be observed mainly in these marketing units or at the headquarters. To examine this possibility, we use data from the Longitudinal Business Database (LBD), which includes employment and payroll information on all establishments in all sectors. We find results consistent with the baseline analysis; in particular, we find significant declines in firm-level employment, and no change in average wage.

Second, we check the robustness of the sharp decline in employment, output, and capital to using an alternative instrumental variables (IV) approach to address endogeneity. Our IV approach draws on Pierce and Schott (2013), who find evidence that the decline in employment in manufacturing was sharper in those industries for which the threat of tariff hikes with China declined the most, following conferral of Permanent Normal Trade Relations (PNTR) on China. Specifically, they find "circumstantial evidence that these changes in employment are driven in part by offshoring." The idea behind our IV approach is that the PNTR status reduces expected costs of offshoring, as expected future tariffs form part of expected transport costs. Because other industry level shocks need to be controlled for, this variation alone does not provide a usable instrument (as reduction of tariff hike threats would get absorbed by industry fixed or industry-year effects). However, any model with a fixed cost of offshoring (e.g., Sethupathy 2011) generates the prediction that reductions in offshoring costs are more likely to affect larger firms, as the smallest firms are not close to the margin for making the switch to offshoring (see Figure **??**). Thus, for our primary IV specification, we use lagged (prior to offshoring) employment levels interacted with the reduction in potential tariffs as an instrument for the offshoring decision. Our first stage results suggest instruments are sufficiently strong, and they also pass the Hansen's overidentification test. The IV results confirm the conclusions from the baseline analysis (the IV results have greater magnitude for the employment and capital reductions, and smaller magnitudes for the sales output and value added).[4]

We also confirmed robustness of our findings to a number of additional concerns, discussed in detail in Section **??**. Thus, in our sample, offshoring was a strong substitute for domestic activity, with output, employment, and capital showing significant declines. Our results appear consistent with shifting of entire product lines abroad, where offshored activity lacked strong vertical linkages with remaining home activities. [5]

Our paper contributes to the literature that has studied whether offshoring is a complement or substitute for domestic employment. Our finding of a stark negative impact on domestic firm output, employment and capital stand in contrast to a number of studies in this literature (which are reviewed in more detail in Section **??** below). Two prominent recent studies are Harrison and McMillan (2011) and Desai, Hines and Foley (2009). In a careful study using MNC survey data from the BEA (which allows them to examine effects separately by destination of outward investment flows), Harrison and McMillan find that in general, offshoring to low-income countries substitutes for domestic employment. Using foreign GDP growth as an instrument, Desai, Hines and Foley (2009) find that foreign investment is generally a complement

[4]The results are also robust to adding lagged capital intensity, white collar and blue collar wage rates and their interactions with the reduction in threat of tariff hikes as additional instruments(though these set of instruments fail the overidentification test).

[5]To check for complementarity, we examined a sub-sample where the activity at the offshored plant was a significant supplier to activities in the remaining plants, per the Input-Output tables (following the approach in Atalay, Hortascu and Syverson 2014). However, we find no significant difference in results for this sub-sample. We interpret this as suggesting that, as documented by Atalay et al (using Commodity flow survey data for the US) and by Ramondo, Rappaport and Ruhl (2014) (using MNC survey data from the Bureau of Economic Analysis (BEA)), actual input flows may not be occurring within firms even when plants appear vertically related per the Input-Output tables.

for domestic investment. The major novelty in our paper is the new linked data that allows us to examine events that are verified (by the U.S. Department of Labor) to be related to offshoring.

The rest of the paper is organized as the following. Section **??** describes the related literature and the alternative approaches to measuring offshoring. Section **??** presents a model of offshoring drawn from Sethupathy (2011)'s extension of the Grossman–Rossi-Hansberg's (2008) work, and briefly discusses the case of horizontal FDI. Section **??** describes the data in more detail. Section **??** briefly describes the empirical methodology used to evaluate the effects of offshoring. Section **??** presents our baseline results. Section **??** describes our robustness checks; Section 8 discusses results and concludes.

2.2 Related Literature and Measurement of Offshoring

The most common approach to measure offshoring in the existing literature is to use the share of imported inputs. At the industry level, this entails using input-output tables to identify offshoring industries. The general consensus in this literature is that employment effects of offshoring are weak. Amiti and Wei (2006) find that the impact is insignificant at the disaggregated level, but positive at a more aggregated level in the U.S. manufacturing sector between 1992 and 2000. In a similar study, Amiti and Wei (2005) find an insignificant employment effect in the U.K. manufacturing industry between 1995 and 2001. For the Canadian manufacturing sector, Morissette and Johnson (2007) find that the industries with intense offshoring did not show significantly different employment growth rates compared to other industries. Koller and Stehrer (2010) use Austrian data and find that offshoring had a negative effect during 1995-2000, but a positive effect during 2000-2003.

Such a measure can also be constructed for firm-level data. For the U.S., the 1987 and 1992 Census of Manufactures conducted by the U.S. Census Bureau collects data on plant-level imported input usage. All manufacturing plants were asked whether they used any inputs of foreign origin. The answer 'yes' is used as a flag for an offshoring activity in many early studies (Berman, Bound and Griliches 1994; Feenstra and Hanson 1996 & 1999; Kurz, 2006). Unfortunately, the Census stopped asking this question after 1992.[6] Similar attempts have been made with micro data of other countries. E.g., Hummels et al.(2011) use Danish employer-employee matched data to explore a similar question with more focus on the impacts on wage rates. They find that offshoring increases high-skilled wages and decreases low-skilled wages, and that workers displaced by offshoring suffer from a larger wage loss than from other layoffs.

An important limitation of using imported input usage as a measure of offshoring is that the imported inputs could be related to newly introduced products rather than replacement of in-house inputs (Feenstra and Markusen 1994). These new inputs would not involve shifting of in-house production, and hence may not capture true offshoring. Further, if an entire production line is offshored, no measured increase in imported inputs will be recorded even though offshoring is taking place; in fact if the offshored activity used some imported inputs, the fraction of inputs imported may even decline. Our data allow us to identify offshoring events certified by an independent investigator, and this avoids these two sources of measurement error that could impact the use of imported intermediate inputs as a proxy for offshoring.

A second source used to identify offshoring is survey data on foreign operations of the U.S. multinationals, collected by the U.S. Bureau of Economic Analysis (BEA). This dataset has detailed operational information at the establishment level, including location, employment and wages. Brainard and Riker (2001) find little substitution between U.S. facilities and foreign affiliates, and larger substitution among foreign affiliates in low wage countries. Stronger substitution between home and foreign affil-

[6] A subsample of establishments were asked this question in the 2007 Census, and used in work by Fort (2011) who investigates the determinants of importing.

iate employment is found by Hanson, Mataloni, and Slaughter (2005). On the other hand, Desai, Foley, and Hines (2009) find complementarity between home and foreign affiliates of U.S. multinationals; they find that when foreign investment (employment compensation) rises by 10%, U.S. domestic investment (employment) rises by 2.6% (3.7%). In contrast, Borga (2005) finds an insignificant effect. Harrison and McMillan (2011) find that while overall offshoring substitutes for domestic employment, the effects of offshoring are nuanced. For firms that do significantly different tasks at home and abroad, foreign and domestic employment are complements, whereas for firms that do similar tasks, foreign and domestic employment are substitutes. Sethupathy (2011) examines offshoring activities to Mexico using the same BEA data. He finds an increase in wages and no evidence of greater job losses in domestic locations at offshoring firms. Similar analysis was performed using the data on European firms. Muendler and Becker (2010) investigate German multinationals and find strong substitution. Braconier and Ekholm (2000) find substitution between Swedish facilities and affiliates in high-income countries, but neither substitution nor complementarity for affiliates in low-income countries.

One drawback of this type of data is that it does not capture the impact of offshoring through arm's length contracts, which according to Bernard et al. (2005), account for about half of offshoring activities of U.S. multinationals. Further, some of the outward investment observed in these data sets, even when they are in vertically-related industries may not be related to offshoring, as they could be related to expansions of activity abroad (rather than shifting of production from home).[7]

[7]E.g., Desai et al (2009) describe their work as investigating the effect of foreign investments broadly (rather than offshoring specifically). While they find that FDI outflows and domestic investments are complementary, earlier work on the effects of foreign investment found mixed effects of foreign operations on domestic activity. A negative link was found for seven selected U.S. multinationals (Stevens and Lipsey, 1992) and for aggregate data in OECD economies (Feldstein, 1995). A positive link was found for cross-section of U.S. multinationals (Lipsey, 1995), aggregate data for Australia (Faeth, 2005), German firm-level data (Kleinert and Toubal, 2010), German industry-level data (Arndt, Buch, and Schnitzer, 2007), and industry-level data for Canada (Hejazi and Pauly, 2001).

The strength of our data is that, because of the nature of the TAA program and classification scheme used by the Department of Labor, we are able to include events of production shifting abroad irrespective of whether it was within the firm or to outside parties. Also, any outbound investments not related to production shifting are not included in our data.

2.3 Theoretical motivation

The theoretical predictions about the effect of offshoring on domestic activity depends crucially on whether the activity is vertically related to the remaining domestic activities of the firm (Harrison and McMillan 2011). We discuss the theoretical background for both vertical and horizontal FDI offshoring, with some more details for a horizontal FDI model with heterogenous firms. Because the nature of fixed costs and marginal cost savings are likely to be similar for both types offshoring, the results about which type of firms benefits from lower offshoring costs is likely to be the similar as well.

2.3.1 A model of vertical FDI offshoring

In this section, we present a brief version of Sethupathy's (2011) extension of Grossman and Rossi-Hansberg's (2008) seminal model of offshoring, where tasks within a vertically linked chain are offshored. While the model in Grossman and Rossi-Hansberg (2008) allows two types of labor, skilled and unskilled, it limits firms to be homogeneous. Sethupathy (2011) allows firm heterogeneity while limiting workers to be homogeneous.

2.3.1.1 Set-up

There are two sectors, X and Y, and one factor, labor. Sector X has homogeneous goods produced using CRS technology. Offshoring is not possible in sector X and the product market is perfectly competitive. Workers are paid their marginal product, w_X. Sector Y has differentiated products with a monopolistically competitive market. Workers first look for a job in sector Y and all residual workers are absorbed by sector X.

First, firms in sector Y incur a sunk entry cost f_e and get a productivity draw ϕ from the Pareto distribution $G(\phi)$. After learning their productivity, firms enter the labor market to hire their workforce and start producing. The production function is $q = \phi N(\phi)$ where $N(\phi)$ denotes the total employment by this firm. Production is composed of a continuum of tasks z with a mass 1 ($z \in [0, 1]$). The employment share of each task is fixed as s. The cost of offshoring task z has two multiplicative components: heterogeneous offshoring cost $t(z)$ and policy cost β. Tasks are indexed according to the size of their offshoring cost so that $t'(z) > 0$. The domestic wage is w_d and the foreign wage rate is w_f. Therefore, the cost of performing task z is sNw_d at home and $\beta t(z)sNw_f$ in the foreign country.

Workers begin their job search in sector Y keeping the job in sector X as an outside option. Firms with productivity ϕ pay a search cost $b(\phi)$ ($b'(\phi) > 0$) and receive a random match. The domestic wage rate in sector Y, w_d, is determined through Nash bargaining between an employer and a worker as the following:

$$\operatorname*{Max}_{w_d} \; \theta ln(w_d - w_x) + (1-\theta) ln(\pi_{op})$$

where π_{op} is the marginal profit of an additional worker and θ denotes the Nash bargaining parameter. This maximization problem yields the rent sharing wage specification as the following:

$$w_d = \eta\pi_{op} + w_x \qquad \text{where } \eta = \frac{\theta}{1-\theta} \text{ : rent sharing parameter}$$

Consumer demand is characterized by the quasi-linear utility function as in Melitz and Ottaviano (2008). Utility maximization yields the following expression for the demand for product i in sector Y:

$$p_i = \rho - \gamma q_i - \lambda Q_y \quad ,$$

where ρ summarizes the degree of substitution among differentiated products in Y, γ indicates the degree of product differentiation, and λ is the degree of substitution between production in X and Y. Q_y denotes the total consumption of sector Y products.

2.3.1.2 Impact of a Fall in Offshoring Cost

As in Melitz (2003), the equilibrium is characterized by cut-off productivities of firms with different operational strategies. In this set-up, we have two cut-off productivities: one for survival and the other for offshoring. This is depicted in panel (a) of Figure **??**. Each offshoring firm then has a marginal task that separates the offshored tasks and domestic activities.

If the policy cost of offshoring, β, decreases, firms with different productivity levels respond differently. These responses are summarized in panel (b) of Figure **??**. First, the cut-off productivity for offshoring falls, since offshoring brings larger cost reduction for all tasks offshored. This implies that offshoring becomes profitable for more firms, including the firms with lower-productivity. Second, the extent of offshoring within an offshoring firm increases. Recall that costs of carrying out task z at home and in the foreign country are sNw_d and $\beta t(z)sNw_f$, respectively. As β falls, the marginal task z^* such that $w_d = \beta t(z^*)w_f$ falls. Therefore, offshoring firms enjoy cost reduction for a larger fraction of their production process. Third, the cut-off productivity for survival increases. Park (2012a) terms this *the cleansing effect of offshoring*. The cost reduction from offshoring reduces the prices of the products by offshoring firms, raising the relative price of the non-offshoring firms. This hurts their profitability, and it becomes harder for non-offshorers to survive.

The employment effect within offshoring firms is ambiguous because there is job creation as well as job destruction. As they initiate offshoring of some tasks, their employment in those tasks at home decreases. However, their prices fall from cost reduction which leads to larger sales. This could lead to job creation, potentially large enough to offset the initial job destruction. The sign of the net effect cannot be determined analytically and depends on parameters of the model (Park, 2012a). The fall in offshoring cost unambiguously improves profitability of offshorers and causes their wage rates to rise through rent-sharing.

Thus this model predicts: (i) an ambiguous net effect on firm-level employment; (ii) positive effect on output; iii) positive effect on wage rates; (iv) positive effect on the survival rate of offshorers relative to non-offshorers. Further, if total factor productivity (TFP) measurement uses common input deflators for all firms within an industry (as we use in this study), measured TFP would increase for offshorers (as they actually face lower input prices, and hence would have relatively lower measured real inputs when a common deflator is used).

In the model above, the positive spillover to domestic output arises due to vertical linkages between the offshored activity and the remaining domestic activity, with the offshored input now being lower cost than before. In general, as discussed in Desai et al (2009), there could be complementarities also if the remaining domestic activity is upstream (e.g., when the more skill or capital intensive activity is retained in the U.S. and labor intensive assembly of final product is offshored abroad). Even in this case, the lower overall cost of production would allow the firm to lower prices and gain market share, leading to an expansion in its domestic activity.

2.3.2 Alternative model: Shifting entire product line (Horizontal FDI)

However, if offshoring consists of a shift of an entire product line (unrelated to remaining domestic activity), foreign employment may simply involve a shift of employment, with no spillover effects. In fact, this type of "horizontal FDI" (H-FDI) could lead to job losses in remaining domestic units, if support activities in other parts of the firm are eliminated following offshoring (Harrison and McMillan 2011, Markusen and Maskus 2001). Further, with H-FDI, measured productivity at the (domestic) firm level would be unaffected, as there is no distinct effect on the marginal costs of other activities.

There would also be no output gain at all if the shift involved movement of export production to another country (termed "export-platform FDI" by Harrison and McMillan, 2011). If part of the shifted production was sold through domestic establishments, there would be gains recorded in output of other domestic units (possibly in marketing units). We investigate this possibility by including non-manufacturing establishments in part of the analysis (see discussion in Section **??**). But if the foreign plant sold directly to other firms directly, the sales would be recorded by the foreign plant, and this would not affect measured output of remaining domestic establishments.

Because the nature of the optimization problem faced by the firm is similar to that discussed above for vertical offshoring, the effect of reduction in offshoring costs can be expected to be similar as well. In particular, if offshoring involves a fixed cost, then offshoring may not be preferred by firms below a cutoff productivity level for whom lowered marginal costs are not sufficient (because of their small scale) to cover the fixed cost. Thus, even for horizontal FDI offshoring, under plausible assumptions, we expect the effect of lowering of the costs of offshoring to be similar to that in Figure **??**.

2.4 Data & TAA Background

We use three main sets of data in our analysis: Trade Adjustment Assistance (TAA) petition data to provide information on layoff events related to offshoring; the

U.S. Census Bureau's Longitudinal Business Database (LBD), with basic operational information on the universe of establishments in the U.S.; and the U.S. Census Bureau's Annual Surveys of Manufactures/Censuses of Manufactures (ASM/CMF) with more detailed information for manufacturing establishments.

2.4.1 Trade Adjustment Assistance Program Background and Data

The information on trade-induced layoffs in U.S. manufacturing plants is obtained from administrative dataof the U.S Department of Labor's (USDOL) TAA program. The bulk of the petition data we use was procured through a Freedom of Information Act request; this was then complemented with manual data collection from TAA websites.[8]

The TAA is a dislocated worker program that originated with the Trade Act of 1974. When layoffs occur, workers or any entity that represents them (company, union, or state) may file a petition with USDOL. The petitions are filed at the plant level. The minimum requirement for petitioning is that three or more workers were laid off or get their work hours reduced. Historically, the majority of petitions were filed by labor unions, but an increasing fraction is being filed by companies. For our sample period - between 1999 and 2006 - 50% of petitions were filed by companies, 42% by unions and workers, and the remaining 8% by State Workforce Office.

The petition filing process is straightforward. The petitioner(s) needs to fill out two-page petition form with basic information about the employer or layoff event such as name and address of the employer, articles produced by the establishment, and the separation dates of the three workers listed on the form. The petition form is available on USDOL website (and can be easily found easily through search engines). The petitioner can fax/mail the form, or file it online at no cost. The petition can be

[8]Some petitions are filed under the North American Free Trade Agreement-Transitional Adjustment Assistance (NAFTA-TAA) program for years between 1994 and 2003. The NAFTA-TAA program was merged into the regular TAA by the Trade Act of 2002.

filed within a year from the separation date.

Once filed, each petition is assigned an investigator from USDOL who conducts interviews at the petitioned plant, upstream/downstream plants, and with customers to identify the reason for layoffs and determine when they began (impact date). Certification is issued if the reason for layoffs is determined to be one of the following: (i) *company imports* (the company itself replaced in-house tasks with imported tasks); (ii) *customer imports* (buyers now purchase from foreign firms instead of this plant); (iii) *production shift* (the company replaced tasks with activities at own subsidiaries abroad); and (iv) *increase in aggregate imports* (an increase in imports of the plant's product at the aggregate level).[9] 45% of petitions in our sample period are denied, as they were deemed not to be trade related. Decisions made on TAA petitions are published in the Federal Register and on the DOL website.

Once certified, the workers displaced from this plant between the impact date and two years from the certification date (or impact date whichever comes later) are eligible for various benefits provided under the TAA program. The benefits, summarized in Appendix Table A.1 (taken from Park 2011), include job training up to 2 years, remedial training, extended unemployment insurance during training, and other financial support such as relocation allowance and job search allowance. It should be noted that the dollar spending on the TAA program is very small relative to other transfer programs (Autor, Dorn and Hanson 2013). Per Autor, et al., per capita in 2007 , in-kind medical transfer programs spent about $2,500, social security retirement insurance about $1,400, disability insurance about $300, federal income assistance about $300, whereas TAA payments amounted to just $2 per capita. Also, a substantial portion of TAA spending was spent on re-employment services, mainly training (see Table B-1 in Collins 2012).

[9]This category (instead of category (ii) customer imports) usually applies when an establishment has many small buyers rather than a few large customers. Many petitions filed in the paper industry were certified for this reason.

Based on the reason for layoffs, we classify the petitions into three groups: offshoring events, import-competition events, and denied petitions. Offshoring events are the petitions certified due to company imports or production shifts (criteria (i) and (iii) above). The layoffs in these events reflect a *voluntary decision* of the company, indicating a strategic move to relocate activity abroad. Import-competition events, instead, are those driven by external forces (categories (ii) and (iv) above).

The petition data report company name, address (state, city, zip code, street address), impact date (the day layoffs began), and 4-digit SIC code. The reason for displacement is reported only after 2002 in the collated data provided by the USDOL in response to our FOIA request (after the Trade Reform Act of 2002 revised the coding guidelines). Though unreported, USDOL had began this classification process prior to 2002; for petitions between 1999 to 2001, we manually examined the investigation report of each certified petition (available on the USDOL website) to identify the reason for certification. We classify a total of 19,603 petitions over our sample's impact years range of 1999 to 2006.[10]

2.4.2 Micro data from the U.S. Census Bureau

We link the information on layoff events from the TAA petition data to confidential micro data from the U.S. Census Bureau. There are two sets of U.S. Census micro data we use to explore firm-level impacts of offshoring. Our primary source is the Annual Surveys and Censuses of Manufactures (ASM/CMF); we conduct some supplementary analysis using the Longitudinal Business Database (LBD).

In order to analyze the impact of offshoring on difefrent aspects of firm-level

[10]Between 1999 and 2006, a total of 23,327 petitions were filed and 12,831 were certified. Of those certified, we were able to identify the reason for layoff for 9,107 petitions. In order to construct the sample of offshoring events and import competition events, we dropped the certified petitions for which the detailed classification was not documented. Thus our final sample includes 9,107 petitions certified with a reason identified and 10,496 denied, totalling 19,603. Table A1 shows the number of certified petitions and offshoring events for each impact year (before cleaning of data to focus on initial offshoring episode for affected firms).

operations, we use ASM/CMF data as our main database. The ASM/CMF contains a rich set of variables such as employment and payroll separately for production and non-production workers, total value of shipments (output), value added, material costs, fixed assets, and investment.

Coverage includes all manufacturing establishments in the Census (CMF) years, and a sub-sample in the ASM years. More specifically, the CMF is a quinquennial survey on the universe of U.S. manufacturing establishments, undertaken in years ending in 2 or 7. For between-Census years, a similar set of information is collected in the ASM for a representative sample of manufacturing establishments. The sampling weight is based on the employment size in the most recent CMF with larger establishments receiving a larger weight. Establishments with 1,000 or more employees, as well as all establishments of multi-unit firms, are included with certainty. The ASM sample changes every five years.

The LBD consists of data on all private, non-farm U.S. establishments in existence that have at least one paid employee, including non-manufacturing establishments, but it collects limited operational information for each plant. The LBD contains annual information on total employment, total payroll, industry, location, and also the birth and exit year for each establishment.[11]

A concern when undertaking analysis with ASM/CMF variables relates to the potential loss of data in the ASM years, and the lack of non-manufacturing establishments in the ASM/CMF. We retain approximately 65% in the ASM/CMF sample compared to our LBD sample. The explanation for why we retain a significant fraction of the LBD sample in the ASM-CMF is twofold: (i) offshoring firms are predominantly engaged in manufacturing activity; and (ii) as we document in Section **??** below, firms (and establishments) that offshore are significantly bigger than average and hence they are disproportionately included in the ASM/CMF. In any case, we

[11] The birth year is left-censored at the start of the data (1976) and the exit year is right censored at the end of our LBD data period (2009).

check robustness of the results to concerns about potential bias from loss of data for ASM years in three ways: (i) in Section **??**, we check robustness of our employment and wage analysis using the LBD sample; (ii) in Section **??**, we examine robustness in a sub-sample of multi-unit firms (all units of multi-unit firms are sampled with certainty in the ASM); and (iii) we examine robustness in a balanced panel of establishments in Section **??**.[12]

2.4.3 Merging of TAA to Census Microdata and Construction of Firm-level Variables

Since TAA petitions are filed at the plant level, the merging of the TAA petition data and the micro data from the Census Bureau is performed at the plant-level. The matching of the names and state information in the petition data to the U.S. Census business register is done using name matching algorithms, supplemented with extensive manual checks and modifications; we provide details on the merging process in the Data Appendix.

Using the firm identification codes available in the Census microdata, we aggregate establishments to one firm. Some firms experienced multiple offshoring events during the observation period, either at different plants at the same time (cross-section) and/or at different times in the observation period (time-series).[13] In such cases, we use the impact date of the first offshoring event as the firm's initiation of offshoring.

We undertake analysis at the firm aggregate level, and use industry or industry-year effects in most specifications. For multi-unit firms, within each firm we aggregate establishment-level employment by 3-digit 1987 SIC codes, and pick the SIC code with the largest employment as the firm's industry. Other firm-level variables (e.g.,

[12]Tests (ii) and (iii) are motivated by other reasons as well, as discussed in the respective sections.

[13]A certified petition covers all workers laid off between the impact date and two years after the certification of the petition. So if the firm continues to layoff workers as part of a staggered offshoring process beyond two years after certification of an initial petition, it would need to file a second petition for the laid off workers to get TAA support.

employment or value added) are aggregates from establishments in the data. Firm level factor intensity measures are obtained using firm-level aggregates of underlying variables (e.g., firm capital intensity is firm level real capital stock divided by firm level real output).

For productivity measurement, we use a number of different approaches: in addition to labor productivity measures (real output per worker and real value added per worker), we also estimate total factor productivity as residuals from a value added production function, estimated alternatively using OLS (with plant-fixed effects) and using the Levinsohn-Petrin (2003) approach to control for endogeneity of inputs. These estimation methods measure TFP at the plant level; in the baseline results reported below, we aggregate productivity measures up to the firm level using the (unweighted) average across all plants at a firm. We check and confirm robustness (unreported) to using an employment-weighted average across all plants, as well as a relative (within-industry) ranking of each of these measures across firms.

2.5 Empirical Methodology

Our main interest is in the firm-level impact of offshoring. While it is expected that the subunit with the offshored activity will see reduction in employment and output, the model sketched out in Section **??** suggests that other domestic units of the offshoring firm would realize benefits from offshoring, so that firm-level employment and output could show improvements in medium- and long-run.

We carry out the impact analysis by exploiting the timing of layoff events identified by our data. In order to separate the operational changes caused by offshoring events from other industry- or even economy-wide factors surrounding the timing of offshoring, we use a difference-in-differences estimation approach, using a matched control group of peer firms. In our baseline analysis we use a 'nearest neighbor' matching, choosing two controls for each offshored firm based on employment within the same industry (as discussed in Section **??**); to undertake the analysis below, the two matched controls are assigned the same event year as the offshored firm. As an alternative robustness check, we use a propensity-score matching approach(as discussed in Section **??** below).

We build a longitudinal link for each treated and control firm for a 13-year window, six years before and after the impact year. We investigate the impacts of offshoring on a range of outcomes including size (sales, value added, employment, and capital), wage rates (overall, production and non-production), factor intensity (capital per employee, non-production share of employment and wage bill), and productivity (labor productivity and TFP measures). An outcome variable, y_{ijt}, of firm i belonging to group j (where one group consists of one *treated* firm and one to two controls) observed at time t is estimated using the following specification:

$$y_{ijt} = \gamma_0 + \sum_{k=-6}^{6} \left(\beta_k \delta_i + \alpha_k\right) D_{j,t+k} + f_i + e_{ijt} \tag{2.1}$$

where $t+k$ is the impact year (the offshoring event occurs k years away from the current time t, with $k \in [-6, 6]$), f_i stands for firm fixed effects, δ_i is an indicator for an offshoring firm, and $D_{j,t+k}$ is the indicator that the treated firm in group j underwent offshoring k periods from year t. In this case, α_k provides the trend for the matched controls, and $(\beta_k + \alpha_k)$ provides the trend for the treated firm. Therefore, β_k captures the impact of offshoring k years from the impact year. We plot the trends (and confidence intervals) for the treatment and control group; these figures provide a straightforward basis to assess: (a) whether there was a clear break in trend around the initiation of offshoring, and (b) to assess whether the offshoring firms and the control group had similar trends before the offshoring event (Angrist and Pischke, 2009 Chapter 5). Note that since the equation is estimated with firm level fixed effects, these estimated coefficients are averages. Standard-errors are clustered by treatment group throughout. We use the year prior to the impact year ($k = -1$) as the omitted year.

To report summary DID effects in regression tables, we collapse the thirteen periods into four groups, two three-year periods prior and two three-year periods after the offshoring event (explained in more detail in section **??** below).[14]

Equation (1) is our preferred specification, as we account for both time-invariant firm-specific characteristics and specific differential effects in the treated firm compared to its controls. In the omitted year, estimates of the variable of interest y_{ijt} will be the same for offshorers and their controls by construction ($\widehat{\gamma}_0$), as the firm fixed effects subsume mean differences. Thus in the results that follow, the comparative differences between the two groups, rather than the absolute magnitude, is the relevant statistic.

2.6 Baseline Results

2.6.1 Cross-Sectional Comparison of Offshorers and Non-offshorers

We first present a basic comparison in firm characteristics between offshorers and non-offshorers prior to offshoring, adopting the approach in Bernard and Jensen's (1999) study of exporters. To restrict attention to the cross-section for which we have maximum data availability, we use 2002 CMF data, and examine differences between (i) firms that have offshoring events in 2003 or later and (ii) the universe of firms that are not linked to any identifiable offshoring event. We do this by regressing dependent variables on an indicator for offshorers, both with and without 3-Digit SIC industry fixed effects.

The results are shown in Table **??**. Our sample of offshorers exhibit premia

[14] As a robustness check, in section **??**, we run regressions with group-period effects (f_{jk}), which allows for industry-size-period specific shocks (but provides only the relative DID estimates, as the control group effects are absorbed by the cell-year effects).

consistent with what is expected in the model presented in Section ??. Offshorers tend to be significantly larger - in terms of sales, value added, employment and capital, both overall (OLS column) and relative to industry peers (Industry FE column). On average they pay higher wages (for both production and non-production workers) and are more capital intensive. They are also more productive, according to most productivity measures.

Interestingly, the non-production wage and employment share measure shows that the offshoring firms are not more skill-intensive than non-offshorers. This is noteworthy given that larger firms are typically both more capital and skill intensive on average; thus future offshorers appear to be significantly less skill-intensive relative to similar-sized firms. This finding is intuitive and consistent with economic theory – we may expect low skill activities to be precisely the ones to be offshored by firms in a developed country, as these activities would be the ones for which there are the largest gains in offshoring to a low-skill abundant developing country (Krugman 2008).

2.6.2 Baseline Analysis: DID using Industry-Size Matched Controls

In order to estimate Equation (1), we construct a control group of "similar" firms. The first approach we take is based on industry and employment size, using the LBD. For each offshoring firm, we use total employment in the year prior to the listed impact year, and select two firms with the closest employment directly above and below the offshoring firm in the same 3-digit SIC industry.[15] Firms that have one or more identified offshoring events are excluded from the control group selection pool. Using the LBD sample for control group selection allows us to take advantage of the fact that the LBD covers the entire universe of firms operating in the U.S.; we thus select control firms from a larger pool of firms to improve the similarity to the treated firms.

[15]We impose a restriction that log employment at one of these 'nearest neighbors' cannot be more than 4 points different from the comparison offshorer, meaning that not every offshorer is paired with exactly two controls.

We then merge this sample of treated and control firms to the detailed data in the ASM/CMF. Table **??** presents results of the difference-in-differences estimation for all firms in our sample with employment-matched controls.

2.6.2.1 Size and Wage Variables

The top rows of Table **??** show the estimation results for size and wage measures. The column headings refer to the time periods. LR-PRE refers to a long run pre-offshoring period; in this context, we take this to be four to six years prior to the offshoring impact year. SR-PRE refers to the short-run pre-offshoring period (one to three years prior to the impact year), SR-POST the short-run post-offshoring period (one to three years after the impact year) and LR-POST the long-run post-offshoring period (four to six years after the impact year). In this specification, the impact year itself is omitted. All size measures - output, value-added, employment and capital - show a large decline in the short-run. We do not find any evidence of improvement in these size measures even in the long run; in fact, all size measures show continuous decline relative to their controls in the long run. We perform a t-test to explore the short-run and long-run impacts compared to the period leading up to the impact year (SR-PRE) rather than the impact year, with results presented in the columns headed with "Relative to SR-PRE". We again find significantly negative impacts in all size measures for offshorers in both the short-run and long-run; the long-run DID decline in output is 0.326 log points or 27.8%, in employment is 0.38 log points or 31.6%, and in capital is 0.253 log points or 22.4%.

Finally, in the last column, we test for evidence of a pre-existing trend in these offshorer-control comparisons that might be accounting for our results. We find no significant differences between the treatment and control group that would indicate trends in these variables prior to the offshoring event. As for firm wage variables, the differential trend between offshorers and non-offshorers are very small and statistically insignificant. This is the case also for the average wage rate, and production and non-production worker wage rates separately.

These results can be seen graphically in Figure **??**. Here we compute coefficients for each event-year (where the omitted event-year is year -1, i.e., one year prior to the offshoring impact year) rather than broader time periods used above. The trend lines for offshorers and the controls with firm fixed effects are shown with 95% confidence bands with standard errors clustered by treatment group. Figure **??** shows that both employment and the total value of shipments for offshoring firms display a drastic decline in the impact year. The event associated with an impact date in the TAA petition data clearly matches a significant layoff event for the firm. More specifically, sub-figure (a) shows that the drastically negative adjustment occurs in the short-run up to four years from the event, then settles at a level that is permanently lower than that of the control group. There is little evidence that employment recovers relative to the control group after the initial adjustment. This implies that if there is any job creation from offshoring, it is out-weighed by continuous downsizing within the firm. Sub-figure (b) shows the same trend for output (sales). The lack of wage impact from offshoring is shown more vividly in sub-figures (c) and (d).

2.6.2.2 Productivity and Factor Intensity

Table **??** also presents results of the difference-in-differences procedure for factor intensity and firm productivity variables. Offshorers do appear to become more capital-intensive than their controls after the offshoring event, which is a result of a smaller decline in capital compared to the larger fall in employment. The share of non-production workers in total employment also rises at offshoring firms, suggesting that layoffs disproportionately affect production workers, consistent with low-skill activities being targeted for offshoring.

For productivity measurements, we use a number of different variables: in addition to labor productivity measures (output per worker and value added per worker), we also estimate total factor productivity as residuals from a value added production function, estimated alternatively using OLS (with plant-fixed effects) and using the Levinsohn-Petrin (2003) approach to controlling for endogeneity of inputs. While the value-added per worker variable shows improvement in both short- and long-run periods after offshoring, no TFP measures show significant improvement. Sub-figures (e) and (f) of Figure **??** present the labor productivity and Levinsohn-Petrin (LP) TFP measures. The TFP measure has a wide confidence band, and appears to show no systematic (DID) change in relative TFP levels, consistent with the results in Table **??**.

2.6.2.3 Firm Survival

If offshoring is beneficial to the firm, one potential consequence is that offshoring firms will be more likely to survive in the highly competitive environment that manufacturing firms face. Figure **??** shows the survival rate of offshoring firms compared to control group firms. This simply depicts the percentage of plants (sub-figure (a)) or firms (sub-figure (b)) in our LBD sample still in existence for the indicated period. The benchmark year is the year prior to the impact year.[16] Within the six years of post-impact observation period, almost 70% of firms disappear from the data.[17] However, the survival rates for offshoring firms and the controls are nearly identical. We find no evidence that offshoring improves the firm's chance of survival.

2.6.3 Potential Selection Bias with TAA Petition Data

Because TAA petitions are triggered by layoffs, our sample of offshoring events captures only events where laid-off workers were not absorbed back into the same

[16] Numbers less than 100% before the impact year indicates that some plants/firms were born between 6 and 1 years prior to their offshoring impact year.

[17] This six year period differs across firms due to the fact that they are aligned around the impact years. They range from 1999 to 2007.

establishment. This raises two potential issues: One, whether this is a valid sample to test the model presented in Section **??**, and two, whether the sample we look at consists of weaker-than-average firms, so that overarching negative trends unrelated to offshoring may be biasing our DID estimates. We believe neither of these concerns apply in our context.

First, we believe our sample is *valid* for testing the model, because the analytical predictions are not based on any particular assumptions about the fate of laid-off workers. In particular, positive spillovers to the rest of the firm do not assume or imply that workers in the offshored activity will be reabsorbed in the same establishment. In fact, it is likely that the offshored tasks systematically differ from the non-offshored tasks, so that workers with skills suitable for the offshored tasks may not be a good fit for the tasks that expand due to gains from offshoring. For example, jobs destroyed due to offshoring could be low-skilled (as the wage advantage for the foreign country is likely to be higher for these tasks) while the newly created jobs may be in relatively high-skilled occupations. Thus workers who used to perform offshored activities are not necessarily likely to be absorbed by the same establishment, under the assumptions of the model. Accordingly, the sample of offshoring events identified using the TAA petition data is a valid one to look for positive spillovers to other parts of the firm.

Second, for every variable of interest, we perform two tests for pre-existing trends. First, following the suggestion in Angrist and Pischke (2009), we examine an event study graph that plots the trend for each of the key outcome variables, both before and after the offshoring event, for both the treatment and control group. As is evident from Figure **??**, all the dependent variables show similar trends for the offshorers and the control group prior to the offshoring event; for employment and output there is a stark break in trend coincident for offshorers coincident with the initiation of offshoring. In particular, there is no evidence of a strong decline in output or sales prior to the offshoring event, in absolute terms or relative to the peer group. Second, we explicitly test for pre-existing trends in our regression analysis (column 7 in Table **??**). None of the dependent variables shows any significant prior trend.

While we believe these tests provide considerable evidence that pre-existing differences in offshoring firm characteristics are not driving the baseline results, we check robustness of our results using an alternative method of constructing a control group – by matching on the propensity score (generated from a model predicting the propensity to offshore). This approach is discussed in detail below.

2.6.3.1 Propensity-matched Controls

We re-select control firms by matching on the propensity score. Specifically, we estimate the probability of offshoring for all firms based on a variety of firm characteristics, and find firms that did not offshore despite having a predicted probability very close to actual offshorers. The potential advantage of this alternative approach is that any post-offshoring effects driven by interaction of pre-existing characteristics with changes in the environment are controlled for by matching on this scalar propensity measure (Rosenbaum and Rubin 1985), assuming certain conditions hold. Specifically, this approach lets us incorporate a number of covariates other than size in forming the control group. First, we estimate the following linear propensity model:

$$Offshore_{ikt} = \beta X_{ikt} + \delta_t + \delta_k + \varepsilon_{ikt} \tag{2.2}$$

We couple the observed offshoring decision (zero or one) for firm i in industry k at time t, $Offshore_{ikt}$ with a vector of firm-level covariates, X_{ikt}, found in the ASM and CMF, including capital intensity, skill intensity, output, and three-year employment and wage growth rates, in order to predict the probability of offshoring given those characteristics. If baseline results are driven by pre-existing differences for offshoring firms on these characteristics, then matching on the propensity score will help control for that bias.

The results from estimation of the propensity model are presented in Table **??**. We find employment growth has no significant predictive power; however wage growth enters negatively, suggesting some prior cost pressure on offshorers. Consistent with the cross-sectional differences documented in Table **??**, we find that higher labor productivity, lower skill-intensity and higher capital intensity predict higher propensity to offshore. Next, we use the predicted propensity to form control groups. and then undertake analysis using Equation **??**.

2.6.3.2 Difference-in-Differences Estimation using Propensity-matched Controls

Table **??** presents results from DID estimation using propensity score matched controls. The results are qualitatively identical to the estimation with employment-matched controls shown in Table **??**. As in the estimation with employment-matched control, all size measures - output, value added, employment, and capital - decline significantly immediately after the impact year and the downward trend continues into the long-run. We perform a t-test to capture the differences between the short-run pre-offshoring period and both the short-run and long-run post-offshoring periods, again finding significant negative differences for offshorers. Finally, in the last column, we test for evidence of any significant pre-offshoring differential trends between the treatment and control groups, and we find none.

The impacts on wage rates are also qualitatively identical to what we found using employment-matched controls. Neither production nor non-production worker wage rates are significantly influenced by offshoring in both short- and long-run.

The bottom panel of Table **??** presents results for factor intensity and productivity measures. Again, the results are qualitatively identical to what we find using employment-matched controls. Offshorers do appear to become more capital-intensive than their controls after the offshoring event, which is again the result of lower decline in capital relative to employment. The share of non-production workers in total employment also rises at offshoring firms. Measures of labor productivity improve - weakly for shipments per worker, more strongly for value added per worker - consistent with a lower decline in output relative to employment. However, again there is little evidence of comparative TFP gains at these offshoring firms compared to their controls in both the short- or long-run.

These results are graphically presented in Figure **??**. All sub-figures display a striking resemblance to Figure **??**. This demonstrates that our results, particularly the lack of evidence for firm-level benefits from offshoring, are not driven by the nature of the control group we selected using employment matching for the baseline analysis.

2.7 Robustness Checks

In order to check the robustness of our results, we perform the same difference-in-differences estimation using various alternative specifications and sub-samples.

2.7.1 Estimation using Treatment Group-Year Fixed Effects

Our baseline regression specifications use firm fixed effects and period effects; while this controls for all possible fixed firm specific effects, the time-varying effects are assumed to effect all controls and offshored firms similarly. In order to allow for group-specific shocks, which effectively allows period effects to vary by industry-size groups, we estimate a variant of Equation (1) that includes group-year fixed effects. The coefficients in these regressions then report variations in offshored firms relative to their matched controls for every period. This set of results on firm performance measures are included in Table **??**, using both employment- and propensity-score-matched controls.

Overall, these results are qualitatively similar to the baseline findings described above, except that changes in skill intensity and labor productivity measures are no longer statistically significant. All size measures decline rapidly compared to the control firms in the short-run. Wage measures show no significant changes. Capital intensity increases, but this is significant only in the propensity-matching analysis; skill intensity measures show no statistically significant changes. Here none of the productivity measures show a significant change following offshoring.

2.7.2 Longitudinal Business Database Results

In this subsection, we use employment and payroll (and hence average wage) data available on all establishments in the LBD, to check robustness of the baseline results to two concerns.

First, it could be the case that employment gains from offshoring are experienced in non-manufacturing establishments of the firm; in particular at the headquarters, or in wholesale or retail establishments of the firm. The latter would be the case if the product offshored was sold in the U.S. through the firm's marketing arm. This would be missed in the baseline analysis that uses manufacturing ASM/CMF data. Because the LBD data includes these data on headquarters as well as marketing (wholesale and retail trade) establishments, using this data would allow us to examine domestic firm-level aggregates that include potential gains in these units.

Second, examining the LBD allows us to check robustness to potential bias from sampling in the ASM, discussed in Section **??**. Because ASM sampling puts more weight on the larger establishments, small establishments in our TAA petition are less likely to be selected into our ASM/CMF sample of offshoring events. Using the LBD sample allows us to check robustness of our findings to potential bias from this sampling procedure.

Table ?? reports results from estimation of Equation (1) using the LBD sample. This raises the sample size from 7,000-9000 offshorer-year observations (depending on the matching technique) to over 12,000. Note that since we drop offshoring firms that cannot be matched to any control, we have different observation counts, even for underlying offshorer-year observations. Such an approach has many fewer observations in the propensity score matching results, as any firm without one of the covariates used to compute the probability of offshoring is excluded. The total number of offshoring events increases from approximately 1,000 (in the ASM/CMF analysis to 1,400 here.

Due to the fact that there is a limited number of operational variables in LBD, we can only perform the analysis on total employment, total payroll, and average wage rate. For propensity score matching analysis with the LBD, we have fewer variables to "match" on, and thus use only employment, wage rate, 3-year employment growth rate, and 3-year wage growth rate as our covariates for Equation (2).

We find results similar to those using the ASM/CMF sample. Employment and total payroll drop greatly compared to the control groups in the short-run and remain low in the long-run. While the magnitude of the long-run effect for employment in the employment-matching approach (-0.138 log points) is lower than the long-run decline in the baseline approach (-0.38 log points in Table ??), the magnitude of decline in the propensity matched approach (-0.366) is very similar to that in the baseline (-0.37 log points in Table ??). The DID effect on average wage rates for offshoring firms is a statistically significant decline of 0.029 log points in the short run, and a gain of 0.061 log points in the long run when we use employment-matched sample; however in the propensity-matched sample we find no statistically significant changes (though magnitudes are similar to that with the employment matched sample). Payroll shows a significant decline, both in the short and long-term, with long-term decline being considerably larger in the propensity-matching analysis.

These results suggest: (i) no significant net employment gains in domestic activities, even including headquarters and marketing units, and no significant increases in wage rates; and (ii) baseline findings for size (employment) and wages are not impacted by loss of data from sampling in the ASM. As discussed in Section 2.4.2, the robustness of the baseline results is not very surprising, given the large degree of overlap between the ASM/CMF and LBD samples.

2.7.3 Multi-Unit Firms

In the model in Section **??**, as some tasks of a firm are offshored, the other tasks that remain at home benefit through the vertical supply links. At the offshored plant itself, the destructive nature of offshoring might dominate any potential job creation making it difficult to capture the positive effects. For single-unit firms, this offshored plant constitutes the offshoring firm.

In this section, we analyze the impact of offshoring using only the multi-unit firms to allow the potential positive effects to be better captured. Close to 80% of our ASM/CMF sample is multi-unit. Table **??** presents the estimation results. The results are qualitatively identical to our baseline analysis of all firms including single-unit firms. Figure **??** shows the trend for total employment and total value of shipments for the estimation using employment-matched controls. One can see that both employment and shipment figures are very similar to subfigures (a) and (b) of Figure **??**.

2.7.4 Pseudo-Firm: Non-offshored Plants in Multi-unit Firms

We take one step deeper into separating the potential positive effects of offshoring from the destructive effects at the offshored plants by looking only at non-offshored plants within the offshoring firms. Specifically, we construct a "pseudo-firm" by aggregating all plants at an offshoring firm that are not matched with any offshoring events from the TAA petition data. We then construct the firm-level variables using only these plants.[18] By construction, only multi-unit firms are candidates to be pseudo-firms. Our sample of offshorer-year observations drops to 2,161, out of over 7,000 offshorer-years in the original sample.

The results are shown in Table **??**. It is clear that even those plants of offshoring firms that are not hit directly by offshoring do not display any sign of gains in size, wages, or productivity compared to their controls. In fact, we find that size variables (output, value added, employment and capital) decline significantly both in the short and long-term for these pseudo-firm aggregates of non-TAA plants within offshoring firms. Wage rates and productivity generally show no significant changes; capital and skill intensity show some increase consistent with the baseline effects.

These results strongly confirm that remaining domestic activity of the offshoring firms in our sample *do not* experience positive spillovers in output, employment, wages or productivity; in fact, the results suggest significant decline in output and employment in unaffected units as well. This is suggestive of elimination of supporting activities in remaining units following offshoring.

2.7.5 Vertical Linkages

As discussed in Section **??**, the vertical supply links between offshored plant and remaining domestic plants is crucial for positive spillovers from offshoring. If there are no vertical linkages, we cannot expect to see improvement in firm-level operation. Thus we could expect to see more gains for firms where the offshored plant is vertically linked to the remaining domestic plants. We check if this is the case in this section.

In order to build the vertical supply links, we use the Input-Output (IO) table of industries for 2007 published by the Bureau of Economic Analysis. The Input-Output

[18] Total employment and firm industry are reconstructed using these non-offshored plants only, then are used to construct the employment-matched controls. The controls selected using propensity-score matching also utilized the variables of the pseudo-firms.

table distinguishes between *Final Products* and *Intermediate Products*, listing the purchase value of each intermediate product used to create a final product. Similar to the procedure outlined in Atalay, Hortacsu, and Syverson (2012), we classify two industries as vertically linked if one industry makes up more than 1% of the total purchase value of all inputs used to produce the final goods. Using the industry code for each establishment, we determine an offshoring firm as vertically linked if the offshored plant is vertically linked to at least one other plant within the firm. About 30% of the original sample fits this definition of vertically-linked offshoring firms. Table **??** summarizes the estimation results. The results for employment and shipments are shown in Figure **??** for employment-matched controls. While the reduction in sample size increases the standard errors of the estimations, the overall pattern of the short-run and long-run impacts is very similar to the ones we find in other specifications.

The lack of significant difference between vertically-linked firms and the others in the wake of offshoring can potentially be explained by the fact that linkages measured using Input-Output tables do not necessarily translate into actual vertical linkages in the form of intra-firm shipments in the data, as carefully documented by Atalay, Hortacsu, and Syverson (2012) using U.S. Commodity Flow Survey data. They find that firms that are identified as vertically-linked rarely use inputs made by other establishments within the firm. Their analysis is for domestic intra-firm shipments in the U.S. manufacturing sector. Ramondo, Rappaport, and Ruhl (2014) look at the cross-border intra-firm shipments of U.S. multinationals using the BEA data. They find that while most multinationals display vertical linkages per the I/O tables, there is very little actual intra-firm shipment. They find that the majority of output from the foreign subsidiaries is sold locally and that the median subsidiary reports no shipment to the U.S. parent. Both studies attribute the identifiable vertical links among establishments without actual shipment to knowledge capital.

This analysis, and the studies cited above, suggest a plausible explanation of our baseline results: vertical linkages across establishments within firms are weak, even if the plant is vertically linked per the IO table. This suggests that the effects of offshoring are likely to be similar to that envisaged in H-FDI models, rather than as in the model sketched in Section **??**.

2.7.6 Balanced Panel Results

Finally, we investigate whether our results are affected by firm entry and exit. In particular, differential patterns of exit by offshoring firms relative to controls could affect the baseline results. For example, short-term exit by the largest offshoring firms could lead to smaller relative sizes for offshorers in the long-term after offshoring.[19]

In order to address this concern, we re-estimate our results using only firms who were present for all 13 years of the 13 year event window (the true balanced panel).[20]. The balanced panel consists of approximately 30% of our baseline sample and contains 2,330 offshorer-years. We find baseline results are robust in this sub-sample – results are available upon request.

2.7.7 Other Robustness Checks

We also undertook a number of additional robustness checks, which we summarize without reporting tables for brevity. First we tried alternative methods for aggregating TFP, as described in Section 4.3. Second, we checked robustness of key results to using only a sample of firms that filed a single offshoring petition in the sample period. Third, we repeated the analysis for only single-unit firms. Fourth, we altered the composition of covariates in the propensity score estimation to exclude 3-year

[19] We note that this bias is controlled for in the analysis with treatment group-year fixed effects in Section **??**, as exiting firms do not contribute to estimated effects (their groups get absorbed by the group-year effects).

[20] ASM/CMF data go up to 2009. In order to retain all six years after offshoring, we need to drop offshoring events that occurred after 2003. Again, our offshoring events in the baseline sample ranges from 1999 to 2006.

growth rates or overall employment. Fifth, we repeated the analysis at the plant level only. Sixth, we checked robustness to examining a subsample of pre-2002 offshorers; results suggest no changes in the pattern of findings over different years. Finally, we performed a number of concurrent checks: multi-unit firms in a balanced panel, pseudo-firms that were vertically linked, pseudo-firms using LBD data. Our baseline results are robust to using these alternative specifications and definitions.

2.8 Discussion and Conclusion

We use specific information on the source of trade-related layoffs available in the assessments of petitions filed under the U.S. Trade Adjustment Assistance program to identify offshoring events. We link these data on initiation of offshoring activity to rich U.S. Census micro datasets, namely the Longitudinal Business Dataset (LBD), Census of Manufactures (CMF), and Annual Survey of Manufactures (ASM). We examine changes in key outcome variables for offshorers relative to controls (matched alternatively on size and propensity score within the same industry) using a standard difference-in-differences methodology.

We find that employment declines significantly at the firm level following offshoring. The DID decline in employment relative to controls is statistically and economically significant – about 19% in the short run and 32% in the longer run. These findings are robust to using alternative control groups. We verify that this is not simply the result of decline at the affected plant; we find that employment falls significantly (only slightly lower in percentage terms than at the affected plants) at aggregated non-affected establishments. This shows that for our sample of offshoring events, offshoring results in net negative employment effects, as well as negative effects at remaining domestic units. While our baseline analysis uses only manufacturing sector data, we obtained similar results using data from the LBD, which covers non-manufacturing establishments as well; there was no employment increase, even including non-manufacturing establishments.

We also examine a number of other outcomes including output, value added, capital, wage rates, labor and total factor productivity, as well as capital and skill intensity using the ASM/CMF data. We find offshoring firms drastically reducing their size (output, value added and capital) compared to controls, with little evidence of increases (or decreases) in productivity or wages. Firms reduce workers more than capital, so capital intensity goes up; this is also reflected in higher labor productivity, but we find no change in more detailed TFP measures relative to the control group.

In the TAA data we observe only those offshoring firms who did not re-absorb their workers ('non-absorbers'); as we argue in Section **??**, even so, we believe that this is a valid sample to check for potential complementarities in other parts of the firm. Further, our figures plotting prior trends for the offshored sample and controls, as well as explicit tests for prior-trends, suggest no strong prior downward trend for offshored firms relative to controls. Nevertheless, our results should be considered as average effects for non-absorbers, rather than for offshorers as a whole.

Our findings suggest that the pathway of vertical linkages crucial in the Grossman and Rossi-Hansberg class of models is not operational in our data. Thus the offshoring activity in our sample may be the shifting of whole product lines abroad, more closely resembling horizontal FDI (H-FDI) in the Markusen and Maskus (2001) model. This type of H-FDI would not result in any positive spillovers, and may generate negative employment and output spillovers, if some supporting activities in other domestic units are closed down following the production shift. In this sense, our results are in line with the findings of Atalay, Hortacsu, and Syverson (2012) and Ramondo, Rappoport and Ruhl (2014) who find very little evidence of intra-firm shipments (even within firms who have establishments in that are vertically linked per the IO tables). Our tentative conclusion that most of our offshoring events may be related to horizontal shifts echoes Ramondo, Rappoport and Ruhl's (2014) conclusion that most foreign affiliate activity is "horizontal" in nature rather than truly vertically linked to domestic activities of MNCs.

One point to keep in mind while interpreting our results are that we focus on the first offshoring event in the sample, while other studies that use imported inputs or MNC data may be looking at changes within existing offshorers. The employment effect of offshoring, even in the case of vertically linked firms, is arguably more negative for new offshorers than for incumbent ones because they go through the initial large-scale job destruction when tasks are first sent abroad. As discussed in Sethupathy (2011), a fall in offshoring cost makes the already-offshored tasks even cheaper, which generates new jobs in domestic operation without necessarily causing any additional displacement in incumbent offshorers. New offshorers do not enjoy this purely positive employment impact. Thus one interpretation of the steep decline we find in employment in the short run could be that this captures the new offshorer's employment adjustment. However, in such models with positive spillovers via vertical linkages, it would be very puzzling to see strong decline in output and employment in the non-affected plants as well.

It should be strongly emphasized that our results *do not* imply negative welfare effects from offshoring. In fact, given data limitations, two of the key channels of gains – reduced output prices and increased global firm profits – are not measured in this paper. Welfare losses from under-utilization of labor resources would depend on the how long the displaced workers take to find new jobs, which we cannot address with this data. We hope to undertake follow-up work to address these issues using different data sources: Comtrade for publicly listed companies to assess impact of offshoring on global profits, and U.S. Census shipment level trade data to measure unit values which can be used for estimating price effects for products exported by offshoring firms. Using the link between TAA and the business register that we have developed, it is also possible to use the U.S. Census' employee-employer linked dataset

(LEHD) to examine unemployment durations and wage effects on workers at affected plants.

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Table 2.1: Comparison of Offshoring Firms to Non-offshorers Prior to Offshoring

Variable	Definition	OLS	Industry FE
Size Measures			
Output	Log(Total Sales)	3.044	2.607
		(0.000)	(0.000)
Value Added	Log(Value Added)	2.919	2.521
		(0.000)	(0.000)
Employment	Log(Employment)	2.679	2.313
		(0.000)	(0.000)
Capital	Log(Capital)	3.336	2.949
		(0.000)	(0.000)
Wage Measures			
Wage Rate	Log(Total Wage Bill/ total employment)	0.045	0.044
		(0.001)	(0.000)
NPW Wage Rate	Log(Non-production wage bill/ employment)	0.082	0.040
		(0.000)	(0.016)
PW Wage Rate	Log(Production wage bill/ production employment)	0.011	0.049
		(0.447)	(0.000)
Factor Intensity			
Capital Intensity	Log(Capital/ total employment)	0.656	0.636
		(0.000)	(0.000)
NPW Emp Share	Non-production share of employment	−0.009	−0.009
		(0.131)	(0.112)
NPW Wage Share	Non-production share of wage bill	0.003	−0.012
		(0.660)	(0.018)
Productivity			
Output per Worker	Log(Total sales/employment)	0.364	0.294
		(0.000)	(0.000)
VA per Worker	Log(Value added/employment)	0.240	0.208
		(0.000)	(0.000)
TFP-Levpet	TFP- Levpet, Value Added	0.088	0.054
		(0.026)	(0.028)
TFP-OLS	TFP- OLS (fixed effects), Value Added	0.618	0.559
		(0.000)	(0.000)

Notes: The number of observations for all of the statistics is 131,377. The p-values are reported in parenthesis. Industry-level fixed effects are at the 3-Digit SIC level. The data source is the Census of Manufactures for 2002.

Table 2.2: Difference-in-Differences Estimation - All Firms, Employment-Matched

					Relative to SR_PRE		Pre-Trend Test
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Size Measures							
Output	0.069	0.048	-0.179	-0.278	-0.227	-0.326	-0.021
	(0.055)	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)	(0.416)
Value Added	0.097	0.075	-0.228	-0.316	-0.303	-0.391	-0.022
	(0.016)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.452)
Employment	0.07	0.041	-0.211	-0.339	-0.252	-0.38	-0.029
	(0.039)	(0.059)	(0.000)	(0.000)	(0.000)	(0.000)	(0.247)
Capital	0.004	0.005	-0.116	-0.248	-0.121	-0.253	0.001
	(0.920)	(0.841)	(0.000)	(0.000)	(0.000)	(0.000)	(0.770)
Wage Measures							
Wage Rate	-0.002	-0.003	-0.004	0.002	-0.001	0.005	-0.001
	(0.834)	(0.711)	(0.719)	(0.904)	(0.980)	(0.701)	(0.892)
NPW Wage Rate	-0.019	-0.003	-0.036	-0.027	-0.033	-0.024	0.016
	(0.373)	(0.865)	(0.046)	(0.254)	(0.051)	(0.272)	(0.337)
PW Wage Rate	0.007	0.008	-0.004	0.006	-0.012	-0.002	0.001
	(0.596)	(0.430)	(0.757)	(0.682)	(0.659)	(0.291)	(0.122)
Factor Intensity							
Capital Intensity	-0.066	-0.046	0.096	0.091	0.142	0.137	0.02
	(0.038)	(0.029)	(0.000)	(0.020)	(0.000)	(0.001)	(0.406)
NPW Emp Share	-0.001	-0.003	0.021	0.022	0.024	0.025	-0.002
	(0.904)	(0.589)	(0.000)	(0.004)	(0.000)	(0.002)	(0.690)
NPW Wage Share	-0.007	-0.003	0.015	0.013	0.018	0.016	0.004
	(0.313)	(0.603)	(0.005)	(0.099)	(0.003)	(0.055)	(0.444)
Productivity							
Output per Worker	0.027	0.034	-0.015	0.024	-0.049	-0.01	0.007
	(0.313)	(0.139)	(0.555)	(0.503)	(0.045)	(0.775)	(0.720)
VA per Worker	-0.002	0.006	0.035	0.062	0.029	0.056	0.008
	(0.936)	(0.689)	(0.043)	(0.017)	(0.117)	(0.033)	(0.585)
TFP- Levpet	0.017	0.049	-0.057	-0.03	-0.106	-0.079	0.032
	(0.589)	(0.055)	(0.040)	(0.453)	(0.000)	(0.052)	(0.156)
TFP- OLS	0.034	0.048	0.016	0.022	-0.032	-0.026	0.014
	(0.267)	(0.060)	(0.549)	(0.603)	(0.023)	(0.519)	(0.506)

Notes: The number of observations for each regression (row) is 22,556. Refer to Table **??** for variable definitions. The column headings refer to time periods. LR-PRE refers to a long run pre-offshoring period (four to six years prior to the offshoring impact year). SR-PRE refers to the short-run pre-offshoring period (one to three years prior to the impact year), SR-POST the short-run post-offshoring period (one to three years after the impact year) and LR-POST the long-run post-offshoring period (four to six years after the impact year). The variables correspond to those in Table 1. All specifications include event-year and firm fixed effects. The figures in parenthesis are p-values.

Table 2.3: Propensity Model Estimates

Variable	Coeff
3-year Employment Growth	0.01
3-year Wage Growth	-0.007^{**}
Output per Worker	0.012^{**}
NPW Emp Share	-0.009^{**}
Capital Intensity	0.012^{**}
Constant	-0.077^{**}
R-sq	0.06

Notes: Dependent variable is a dummy=1 if the firm offshored in any year in the sample period. Refer to Table **??** for variable definitions. Number of observations is 16,296. ** denotes significance at 1% level and * at 5% level.

Table 2.4: Difference-in-Differences Estimation - All Firms, Propensity Score Matching

					Relative to SR_PRE		**PE Trend Test**
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Size Measures							
Output	-0.019	0.016	-0.128	-0.239	-0.144	-0.255	0.035
	(0.624)	(0.529)	(0.000)	(0.000)	(0.000)	(0.000)	(0.228)
Value Added	0.035	0.061	-0.159	-0.295	-0.22	-0.356	0.026
	(0.424)	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.412)
Employment	-0.011	0.011	-0.193	-0.359	-0.204	-0.37	0.022
	(0.741)	(0.624)	(0.000)	(0.000)	(0.000)	(0.000)	(0.392)
Capital	0.019	-0.019	-0.052	-0.171	-0.033	-0.152	-0.038
	(0.660)	(0.484)	(0.073)	(0.003)	(0.288)	(0.009)	(0.239)
Wage Measures							
Wage Rate	-0.011	-0.008	0.007	0.037	0.015	0.045	0.003
	(0.384)	(0.412)	(0.503)	(0.015)	(0.145)	(0.002)	(0.731)
NPW Wage Rate	0.011	-0.006	-0.009	0.053	-0.003	0.059	-0.017
	(0.674)	(0.757)	(0.674)	(0.072)	(0.870)	(0.030)	(0.374)
PW Wage Rate	-0.028	-0.015	0.001	0.009	0.016	0.024	0.013
	(0.048)	(0.187)	(0.992)	(0.603)	(0.185)	(0.131)	(0.238)
Factor Intensity							
Capital Intensity	0.031	-0.03	0.141	0.188	0.171	0.218	-0.061
	(0.379)	(0.190)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)
NPW Emp Share	-0.006	-0.003	0.016	0.021	0.019	0.024	0.003
	(0.379)	(0.610)	(0.003)	(0.016)	(0.001)	(0.008)	(0.510)
NPW Wage Share	0.001	-0.002	0.016	0.03	0.018	0.032	-0.003
	(0.992)	(0.734)	(0.008)	(0.002)	(0.007)	(0.001)	(0.761)
Productivity							
Output per Worker	0.047	0.05	0.034	0.063	-0.016	0.013	0.003
	(0.114)	(0.059)	(0.219)	(0.129)	(0.562)	(0.735)	(0.876)
VA per Worker	-0.007	0.004	0.065	0.119	0.061	0.115	0.011
	(0.741)	(0.803)	(0.000)	(0.000)	(0.001)	(0.000)	(0.462)
TFP- Levpet	-0.012	0.025	-0.043	0.009	-0.068	-0.016	0.037
	(0.734)	(0.384)	(0.177)	(0.841)	(0.025)	(0.712)	(0.130)
TFP- OLS	-0.031	0.023	0.017	0.064	-0.006	0.041	0.054
	(0.384)	(0.424)	(0.589)	(0.177)	(0.856)	(0.348)	(0.029)

Notes: The number of observations for each regression (row) is 18,949. Refer to Table **??** for variable definitions. See notes to Table **??** for explanation of column titles. All specifications include firm fixed effects and event-year effects; the figures in parenthesis are p-values.

Table 2.5: Difference-in-Differences Estimation - All Firms, Treatment Group-Year Fixed Effects

	Employment-Matched							**Propensity-Matched**						
					Relative to SR_PRE		**PE Trend Test**					**Relative to SR_PRE**		**PE Trend Test**
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Size Measures														
Output	0.081	0.05	-0.132	-0.253	-0.182	-0.303	-0.031	-0.123	0.038	-0.25	-0.224	-0.288	-0.262	0.161
	(0.177)	(0.285)	(0.007)	(0.004)	(0.001)	(0.001)	(0.497)	(0.129)	(0.529)	(0.001)	(0.072)	(0.004)	(0.036)	(0.003)
Value Added	0.117	0.079	-0.167	-0.251	-0.246	-0.33	-0.038	-0.062	0.091	-0.248	-0.267	-0.339	-0.358	0.153
	(0.069)	(0.126)	(0.004)	(0.009)	(0.000)	(0.001)	(0.444)	(0.465)	(0.168)	(0.003)	(0.043)	(0.000)	(0.007)	(0.008)
Employment	0.093	0.041	-0.17	-0.263	-0.211	-0.304	-0.052	-0.104	0.018	-0.262	-0.311	-0.28	-0.329	0.122
	(0.067)	(0.242)	(0.000)	(0.000)	(0.000)	(0.000)	(0.199)	(0.156)	(0.741)	(0.000)	(0.006)	(0.000)	(0.004)	(0.015)
Capital	0.047	0.001	-0.082	-0.235	-0.083	-0.236	-0.046	-0.099	-0.024	-0.154	-0.178	-0.13	-0.154	0.075
	(0.549)	(0.992)	(0.208)	(0.027)	(0.194)	(0.033)	(0.457)	(0.267)	(0.704)	(0.052)	(0.197)	(0.115)	(0.260)	(0.242)
Wage Measures														
Wage Rate	-0.009	-0.002	0.007	-0.019	0.009	-0.017	0.007	-0.014	0.001	-0.02	0.014	-0.021	0.013	0.015
	(0.667)	(0.904)	(0.704)	(0.484)	(0.617)	(0.514)	(0.662)	(0.472)	(0.984)	(0.254)	(0.976)	(0.225)	(0.583)	(0.292)
NPW Wage Rate	-0.022	-0.003	-0.024	-0.04	-0.021	-0.037	0.019	0.012	0.011	-0.026	0.043	-0.037	0.032	-0.001
	(0.516)	(0.912)	(0.401)	(0.303)	(0.413)	(0.298)	(0.471)	(0.719)	(0.682)	(0.368)	(0.162)	(0.162)	(0.382)	(0.941)
PW Wage Rate	0.002	-0.006	0.004	-0.005	0.01	0.001	-0.008	-0.019	-0.005	-0.013	0.003	-0.008	0.008	0.014
	(0.920)	(0.726)	(0.865)	(0.865)	(0.619)	(0.957)	(0.610)	(0.379)	(0.772)	(0.497)	(0.920)	(0.654)	(0.767)	(0.380)
Factor Intensity														
Capital Intensity	-0.046	-0.041	0.088	0.029	0.129	0.07	0.005	0.004	-0.042	0.108	0.132	0.15	0.174	-0.046
	(0.472)	(0.435)	(0.126)	(0.741)	(0.014)	(0.425)	(0.909)	(0.928)	(0.238)	(0.013)	(0.082)	(0.000)	(0.018)	(0.245)
NPW Emp Share	-0.004	-0.002	0.016	0.015	0.018	0.017	0.002	-0.005	-0.002	0.006	0.016	0.008	0.018	0.003
	(0.667)	(0.779)	(0.095)	(0.327)	(0.060)	(0.252)	(0.803)	(0.624)	(0.834)	(0.549)	(0.294)	(0.452)	(0.235)	(0.650)
NPW Wage Share	-0.008	-0.001	0.014	0.008	0.015	0.009	0.007	-0.001	0.001	0.003	0.023	0.002	0.022	0.002
	(0.490)	(0.912)	(0.208)	(0.603)	(0.188)	(0.562)	(0.437)	(0.920)	(0.992)	(0.749)	(0.156)	(0.751)	(0.146)	(0.899)
Productivity														
Output per Worker	0.025	0.038	0.004	0.012	-0.034	-0.026	0.013	0.041	0.073	0.014	0.044	-0.059	-0.029	0.032
	(0.582)	(0.332)	(0.936)	(0.849)	(0.405)	(0.669)	(0.694)	(0.332)	(0.052)	(0.734)	(0.478)	(0.132)	(0.601)	(0.274)
VA per Worker	-0.012	0.009	0.038	0.011	0.029	0.002	0.021	-0.02	0.02	0.012	0.087	-0.008	0.067	0.04
	(0.772)	(0.787)	(0.276)	(0.841)	(0.390)	(0.968)	(0.467)	(0.575)	(0.484)	(0.704)	(0.064)	(0.795)	(0.143)	(0.100)
TFP- Levpet	0.068	0.096	-0.029	0.002	-0.125	-0.094	0.028	0.029	0.077	-0.054	-0.01	-0.131	-0.087	0.048
	(0.150)	(0.020)	(0.555)	(0.976)	(0.007)	(0.177)	(0.402)	(0.624)	(0.057)	(0.267)	(0.889)	(0.004)	(0.199)	(0.119)
TFP- OLS	0.055	0.076	-0.014	-0.039	-0.09	-0.115	0.021	-0.029	0.056	-0.028	0.031	-0.084	-0.025	0.085
	(0.246)	(0.075)	(0.772)	(0.617)	(0.062)	(0.139)	(0.514)	(0.555)	(0.184)	(0.555)	(0.682)	(0.066)	(0.722)	(0.010)

Notes: The number of observations for the employment-matched sample regressions (first seven columns in each row) is 22,556, and for the propensity-matched sample regressions (last seven columns in each row) is 18,949. Refer to Table **??** for variable definitions. See notes to Table **??** for explanation of column titles. All specifications include treatment group-year fixed effects and a treatment dummy; the figures in parenthesis are p-values.

Table 2.6: Difference-in-Differences Estimation - LBD Sample

	Employment-Matched							**Propensity-Matched**						
					Relative to SR_PRE		**PE Trend Test**					**Relative to SR_PRE**		**PE Trend Test**
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Employment	0.116	-0.001	-0.293	-0.431	-0.292	-0.138	-0.117	0.028	0.005	-0.226	-0.361	-0.231	-0.366	-0.023
	(0.000)	(0.960)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.610)	(0.912)	(0.000)	(0.000)	(0.000)	(0.000)	(0.581)
Wage Rate	-0.024	0.013	-0.016	0.045	-0.029	0.061	0.037	0.034	0.004	-0.025	0.062	-0.029	0.058	-0.03
	(0.165)	(0.352)	(0.368)	(0.085)	(0.012)	(0.001)	(0.017)	(0.131)	(0.857)	(0.263)	(0.031)	(0.137)	(0.701)	(0.072)
Payroll	0.117	0.013	-0.315	-0.366	-0.328	-0.051	-0.104	0.076	0.023	-0.237	-0.289	-0.26	-0.312	-0.053
	(0.000)	(0.447)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.174)	(0.653)	(0.000)	(0.000)	(0.000)	(0.000)	(0.201)

Notes: The number of observations for the employment-matched sample regressions (first seven columns in each row) is 37,207, and for the propensity-matched sample regressions (last seven columns in each row) is 33,393. Refer to Table **??** for variable definitions. See notes to Table **??** for explanation of column titles. All specifications include firm fixed effects and event-year effects; the figures in parenthesis are p-values.

Table 2.7: Difference-in-Differences Estimation - Multi-Unit Firms Only

	Employment-Matched							Propensity-Matched						
					Relative to SR_PRE		PE Trend Test					Relative to SR_PRE		PE Trend Test
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Size Measures														
Output	0.032	0.024	0.171	-0.292	0.147	-0.316	-0.008	-0.032	0.006	-0.119	-0.247	-0.125	-0.253	0.038
	(0.407)	(0.368)	(0.000)	(0.000)	(0.000)	(0.000)	(0.768)	(0.430)	(0.826)	(0.000)	(0.000)	(0.000)	(0.000)	(0.229)
Value Added	0.066	0.054	-0.216	-0.332	-0.27	-0.386	-0.012	0.035	0.056	-0.143	-0.288	-0.199	-0.344	0.021
	(0.134)	(0.089)	(0.000)	(0.000)	(0.000)	(0.000)	(0.716)	(0.459)	(0.091)	(0.000)	(0.000)	(0.000)	(0.000)	(0.540)
Employment	0.044	0.017	-0.195	-0.335	-0.212	-0.352	-0.027	-0.017	0.003	-0.184	-0.362	-0.187	-0.365	0.02
	(0.238)	(0.459)	(0.000)	(0.000)	(0.000)	(0.000)	(0.332)	(0.660)	(0.904)	(0.000)	(0.000)	(0.000)	(0.000)	(0.506)
Capital	-0.017	-0.026	-0.12	-0.258	-0.094	-0.232	-0.009	0.005	-0.026	-0.056	-0.174	-0.03	-0.148	-0.031
	(0.704)	(0.347)	(0.000)	(0.000)	(0.003)	(0.000)	(0.778)	(0.920)	(0.373)	(0.072)	(0.004)	(0.367)	(0.018)	(0.398)
Wage Measures														
Wage Rate	-0.003	-0.004	-0.001	0.001	0.003	0.005	-0.001	-0.011	-0.009	0.003	0.028	0.012	0.037	0.002
	(0.795)	(0.689)	(0.889)	(0.920)	(0.826)	(0.701)	(0.922)	(0.363)	(0.332)	(0.764)	(0.070)	(0.256)	(0.014)	(0.783)
NPW Wage Rate	-0.013	0.008	-0.024	-0.022	-0.032	-0.03	0.021	0.014	-0.013	-0.002	0.045	0.011	0.058	-0.027
	(0.562)	(0.660)	(0.201)	(0.358)	(0.068)	(0.178)	(0.225)	(0.582)	(0.497)	(0.912)	(0.136)	(0.614)	(0.039)	(0.161)
PW Wage Rate	0.006	-0.011	-0.004	0.004	0.007	0.015	-0.017	-0.028	-0.016	-0.003	0.001	0.013	0.017	0.012
	(0.646)	(0.294)	(0.749)	(0.779)	(0.492)	(0.280)	(0.094)	(0.055)	(0.142)	(0.810)	(0.952)	(0.252)	(0.286)	(0.332)
Factor Intensity														
Capital Intensity	-0.06	-0.043	0.075	0.077	0.118	0.12	0.017	0.021	-0.029	0.127	0.188	0.156	0.217	-0.05
	(0.064)	(0.048)	(0.002)	(0.060)	(0.000)	(0.004)	(0.489)	(0.562)	(0.230)	(0.000)	(0.000)	(0.000)	(0.000)	(0.073)
NPW Emp Share	-0.004	-0.005	0.018	0.02	0.023	0.025	-0.001	-0.009	-0.001	0.013	0.015	0.014	0.016	0.008
	(0.478)	(0.317)	(0.000)	(0.012)	(0.000)	(0.002)	(0.926)	(0.159)	(0.897)	(0.020)	(0.091)	(0.028)	(0.089)	(0.095)
NPW Wage Share	-0.009	-0.003	0.014	0.013	0.017	0.016	0.006	-0.003	-0.001	0.015	0.025	0.016	0.026	0.002
	(0.187)	(0.589)	(0.009)	(0.131)	(0.006)	(0.078)	(0.255)	(0.726)	(0.897)	(0.017)	(0.010)	(0.026)	(0.010)	(0.735)
Productivity														
Output per Worker	0.021	0.037	-0.019	0.003	-0.056	-0.034	0.016	0.051	0.053	0.04	0.073	-0.013	0.02	0.002
	(0.447)	(0.121)	(0.459)	(0.928)	(0.029)	(0.349)	(0.450)	(0.095)	(0.050)	(0.159)	(0.084)	(0.646)	(0.612)	(0.933)
VA per Worker	-0.013	0.006	0.026	0.044	0.02	0.038	0.019	-0.015	0.003	0.064	0.114	0.061	0.111	0.018
	(0.549)	(0.704)	(0.136)	(0.099)	(0.288)	(0.162)	(0.218)	(0.484)	(0.881)	(0.000)	(0.000)	(0.001)	(0.000)	(0.287)
TFP- Levpet	0.01	0.053	-0.056	-0.044	-0.109	-0.097	0.043	-0.007	0.03	-0.043	0.016	-0.073	-0.014	0.037
	(0.757)	(0.046)	(0.054)	(0.298)	(0.000)	(0.023)	(0.067)	(0.841)	(0.317)	(0.204)	(0.734)	(0.024)	(0.752)	(0.153)
TFP- OLS	0.032	0.053	-0.021	-0.015	-0.074	-0.068	0.021	-0.016	0.034	0.025	0.081	-0.009	0.047	0.05
	(0.317)	(0.048)	(0.459)	(0.734)	(0.013)	(0.120)	(0.361)	(0.667)	(0.250)	(0.447)	(0.097)	(0.766)	(0.305)	(0.054)

Notes: The number of observations for the employment-matched sample regressions (first seven columns in each row) is 19,245, and for the propensity-matched sample regressions (last seven columns in each row) is 16,066. Refer to Table **??** for variable definitions. See notes to Table **??** for explanation of column titles. All specifications include firm fixed effects and event-year effects; the figures in parenthesis are p-values.

Table 2.8: Difference-in-Differences Estimation - Pseudo-Firms

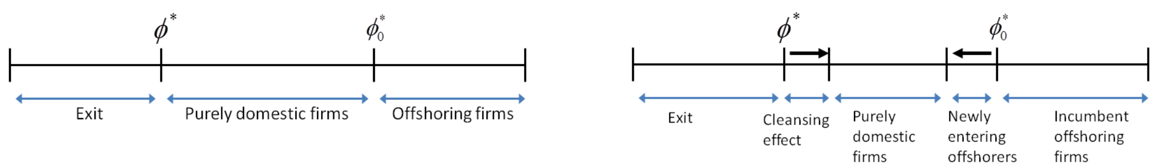
	Employment-Matched							Propensity-Matched						
					Relative to SR_PRE		**PE Trend Test**					**Relative to SR_PRE**		**PE Trend Test**
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Size Measures														
Output	0.12	0.068	-0.185	-0.262	-0.253	-0.33	-0.052	0.02	0.035	-0.132	-0.208	-0.167	-0.243	0.015
	(0.006)	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)	(0.072)	(0.631)	(0.222)	(0.000)	(0.000)	(0.000)	(0.000)	(0.624)
Value Added	0.148	0.075	-0.211	-0.298	-0.286	-0.373	-0.073	0.072	0.088	-0.151	-0.229	-0.239	-0.317	0.016
	(0.001)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.134)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)	(0.633)
Employment	0.139	0.062	-0.178	-0.271	-0.24	-0.333	-0.077	0.024	0.028	-0.175	-0.313	-0.203	-0.341	0.004
	(0.001)	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.535)	(0.294)	(0.000)	(0.000)	(0.000)	(0.000)	(0.897)
Capital	0.084	0.031	-0.147	-0.188	-0.178	-0.219	-0.053	0.07	0.005	-0.104	-0.181	-0.109	-0.186	-0.065
	(0.080)	(0.337)	(0.000)	(0.000)	(0.000)	(0.000)	(0.128)	(0.134)	(0.889)	(0.002)	(0.001)	(0.002)	(0.002)	(0.062)
Wage Measures														
Wage Rate	-0.022	-0.018	-0.007	-0.009	0.011	0.009	0.004	0.016	-0.016	0.002	0.005	0.018	0.021	-0.032
	(0.077)	(0.066)	(0.522)	(0.535)	(0.304)	(0.504)	(0.682)	(0.246)	(0.112)	(0.873)	(0.741)	(0.099)	(0.462)	(0.966)
NPW Wage Rate	-0.028	-0.026	-0.017	-0.023	0.009	0.003	0.002	-0.007	-0.026	-0.001	0.012	0.025	0.038	-0.019
	(0.208)	(0.134)	(0.373)	(0.358)	(0.628)	(0.896)	(0.923)	(0.803)	(0.204)	(0.952)	(0.682)	(0.235)	(0.189)	(0.314)
PW Wage Rate	-0.006	-0.014	-0.004	0.004	0.01	0.018	-0.008	-0.018	-0.012	-0.004	-0.02	0.008	-0.008	0.006
	(0.674)	(0.230)	(0.741)	(0.818)	(0.379)	(0.240)	(0.464)	(0.254)	(0.332)	(0.779)	(0.267)	(0.479)	(0.649)	(0.637)
Factor Intensity														
Capital Intensity	-0.038	-0.022	0.034	0.101	0.056	0.123	0.016	0.046	-0.023	0.071	0.132	0.094	0.155	-0.069
	(0.289)	(0.368)	(0.973)	(0.022)	(0.064)	(0.004)	(0.541)	(0.201)	(0.347)	(0.012)	(0.003)	(0.001)	(0.001)	(0.010)
NPW Emp Share	-0.004	-0.003	0.012	0.015	0.015	0.018	0.001	-0.004	-0.005	0.002	0.007	0.007	0.012	-0.001
	(0.569)	(0.610)	(0.040)	(0.052)	(0.012)	(0.021)	(0.797)	(0.569)	(0.379)	(0.757)	(0.412)	(0.256)	(0.177)	(0.859)
NPW Wage Share	-0.011	-0.006	0.01	0.007	0.016	0.013	0.005	-0.006	-0.009	0.002	0.014	0.011	0.023	-0.003
	(0.159)	(0.298)	(0.134)	(0.412)	(0.021)	(0.126)	(0.398)	(0.459)	(0.107)	(0.719)	(0.156)	(0.072)	(0.017)	(0.508)
Productivity														
Output per Worker	0.023	0.027	-0.024	-0.021	-0.051	-0.048	0.004	0.05	0.061	0.024	0.084	-0.037	0.023	0.011
	(0.447)	(0.242)	(0.358)	(0.569)	(0.061)	(0.175)	(0.848)	(0.142)	(0.028)	(0.424)	(0.043)	(0.187)	(0.563)	(0.607)
VA per Worker	-0.019	0.004	-0.006	0.005	-0.01	0.001	0.023	-0.002	0.008	0.043	0.105	0.035	0.097	0.01
	(0.430)	(0.818)	(0.779)	(0.841)	(0.657)	(0.957)	(0.190)	(0.920)	(0.667)	(0.022)	(0.000)	(0.086)	(0.001)	(0.551)
TFP- Levpet	0.028	0.033	-0.012	-0.014	-0.045	-0.047	0.005	-0.012	0.024	0.005	0.061	-0.019	0.037	0.036
	(0.447)	(0.238)	(0.674)	(0.741)	(0.167)	(0.290)	(0.843)	(0.749)	(0.412)	(0.873)	(0.204)	(0.555)	(0.436)	(0.151)
TFP- OLS	0.041	0.044	0.01	0.03	-0.034	-0.014	0.003	-0.03	0.033	0.031	0.072	-0.002	0.039	0.063
	(0.242)	(0.116)	(0.726)	(0.478)	(0.275)	(0.753)	(0.890)	(0.418)	(0.276)	(0.332)	(0.129)	(0.948)	(0.393)	(0.009)

Notes: The number of observations for the employment-matched sample regressions (first seven columns in each row) is 18,431, and for the propensity-matched sample regressions (last seven columns in each row) is 15,882. Refer to Table **??** for variable definitions. See notes to Table **??** for explanation of column titles. All specifications include firm fixed effects and event-year effects; the figures in parenthesis are p-values.

Table 2.9: Difference-in-Differences Estimation - Vertically Related Firms Only

	Employment-Matched							Propensity-Matched						
					Relative to SR_PRE		**PE Trend Test**					**Relative to SR_PRE**		**PE Trend Test**
	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE	LR_PRE	SR_PRE	SR_POST	LR_POST	SR_POST - SR_PRE	LR_POST- SR_PRE	SR_PRE- LR_PRE
Size Measures														
Output	-0.07	-0.02	-0.188	-0.302	-0.168	-0.282	0.05	-0.104	-0.004	-0.071	-0.22	-0.067	-0.216	0.1
	(0.337)	(0.667)	(0.000)	(0.000)	(0.001)	(0.001)	(0.336)	(0.134)	(0.928)	(0.119)	(0.003)	(0.143)	(0.005)	(0.064)
Value Added	-0.07	-0.012	-0.207	-0.344	-0.195	-0.332	0.058	-0.072	0.034	-0.078	-0.314	-0.112	-0.348	0.106
	(0.374)	(0.818)	(0.000)	(0.000)	(0.000)	(0.000)	(0.295)	(0.327)	(0.490)	(0.136)	(0.000)	(0.040)	(0.000)	(0.058)
Employment	-0.01	0.014	-0.156	-0.295	-0.17	-0.309	0.024	-0.085	0.004	-0.084	-0.28	-0.088	-0.284	0.089
	(0.889)	(0.757)	(0.000)	(0.000)	(0.001)	(0.000)	(0.632)	(0.190)	(0.928)	(0.063)	(0.000)	(0.053)	(0.000)	(0.066)
Capital	-0.09	-0.024	-0.163	-0.252	-0.139	-0.228	0.066	-0.035	0.031	-0.021	-0.128	-0.052	-0.159	0.066
	(0.271)	(0.638)	(0.000)	(0.001)	(0.019)	(0.010)	(0.303)	(0.697)	(0.535)	(0.660)	(0.162)	(0.353)	(0.101)	(0.339)
Wage Measures														
Wage Rate	-0.004	-0.007	0.003	0.028	0.01	0.035	-0.003	0.008	0.01	0.014	0.045	0.004	0.035	0.002
	(0.834)	(0.603)	(0.834)	(0.139)	(0.474)	(0.044)	(0.769)	(0.675)	(0.509)	(0.363)	(0.027)	(0.791)	(0.084)	(0.935)
NPW Wage Rate	0.012	0.021	0.018	0.036	-0.003	0.015	0.009	0.023	-0.008	0.02	0.069	0.028	0.077	-0.031
	(0.682)	(0.384)	(0.407)	(0.246)	(0.904)	(0.634)	(0.707)	(0.555)	(0.779)	(0.509)	(0.093)	(0.377)	(0.048)	(0.326)
PW Wage Rate	-0.002	-0.018	-0.01	0.009	0.008	0.027	-0.016	-0.019	0.005	0.009	0.024	0.004	0.019	0.024
	(0.904)	(0.254)	(0.535)	(0.719)	(0.609)	(0.200)	(0.506)	(0.478)	(0.772)	(0.617)	(0.332)	(0.823)	(0.432)	(0.300)
Factor Intensity														
Capital Intensity	-0.081	-0.038	-0.007	0.043	0.031	0.081	0.043	0.05	0.027	0.062	0.152	0.035	0.125	-0.023
	(0.124)	(0.289)	(0.849)	(1.559)	(0.466)	(0.179)	(0.322)	(0.441)	(0.472)	(0.136)	(0.026)	(0.454)	(0.089)	(0.658)
NPW Emp Share	-0.005	-0.006	0.006	0.023	0.012	0.029	-0.001	-0.001	0.002	0.004	0.015	0.002	0.013	0.003
	(0.624)	(0.441)	(0.390)	(0.033)	(0.160)	(0.013)	(0.833)	(0.952)	(0.834)	(0.617)	(0.230)	(0.840)	(0.329)	(0.766)
NPW Wage Share	-0.008	-0.002	0.01	0.028	0.012	0.03	0.006	0.002	0.00	0.007	0.024	0.007	0.024	-0.00199
	(0.522)	(0.787)	(0.250)	(0.024)	(0.203)	(0.018)	(0.574)	(0.897)	(0.992)	(0.441)	(0.084)	(0.536)	(0.114)	(0.866)
Productivity														
Output per Worker	-0.06	-0.026	-0.049	-0.049	-0.023	-0.023	0.034	0.014	0.031	0.004	-0.034	-0.027	-0.065	0.017
	(0.177)	(0.509)	(0.254)	(0.441)	(0.537)	(0.678)	(0.286)	(0.757)	(0.453)	(0.920)	(0.576)	(0.503)	(0.244)	(0.592)
VA per Worker	-0.06	-0.034	-0.03	-0.007	0.004	0.027	0.026	-0.019	-0.008	0.012	0.059	0.02	0.067	0.011
	(0.107)	(0.246)	(0.303)	(0.873)	(0.885)	(0.519)	(0.291)	(0.603)	(0.795)	(0.682)	(0.165)	(0.484)	(0.097)	(0.683)
TFP- Levpet	-0.02	0.00	0.08	0.083	0.08	0.083	0.02	0.024	0.014	0.019	-0.038	0.005	-0.052	-0.01
	(0.682)	(0.992)	(0.070)	(0.165)	(0.094)	(0.172)	(0.581)	(0.667)	(0.749)	(0.675)	(0.582)	(0.918)	(0.727)	(0.790)
TFP- OLS	0.01	0.012	-0.053	-0.069	-0.065	-0.081	0.002	-0.039	0.015	0.01	-0.039	-0.005	-0.054	0.054
	(0.849)	(0.779)	(0.250)	(0.342)	(0.197)	(0.286)	(0.958)	(0.497)	(0.734)	(0.841)	(0.562)	(0.912)	(0.411)	(0.191)

Notes: The number of observations for the employment-matched sample regressions (first seven columns in each row) is 5,935, and for the propensity-matched sample regressions (last seven columns in each row) is 5,546. Refer to Table **??** for variable definitions. See notes to Table **??** for explanation of column titles. All specifications include firm fixed effects and event-year effects; the figures in parenthesis are p-values.

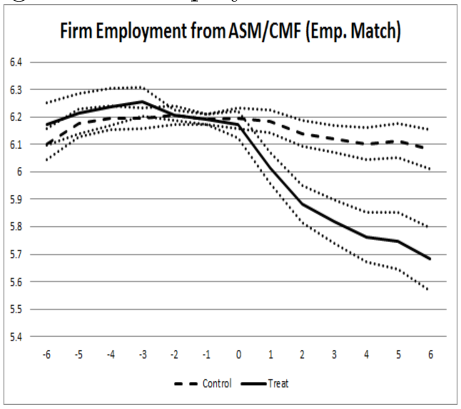


(a) Initial Benchmark Equilibrium

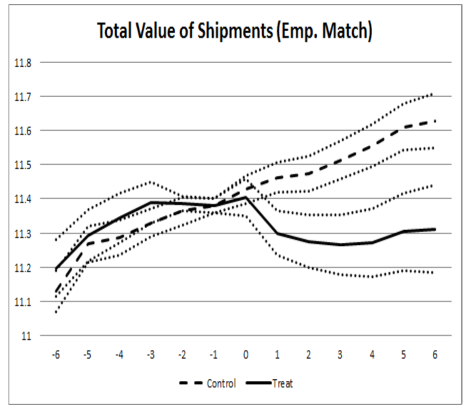
(b) A Fall in Offshoring Cost

Figure 2.1: Cut-off Productivities in Equilibria

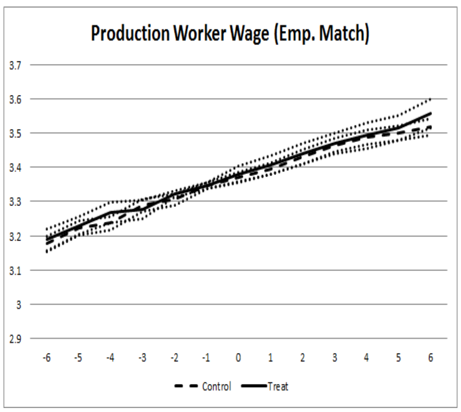
Figure 2.2: Employment-Matched Difference-in-differences Estimation Results



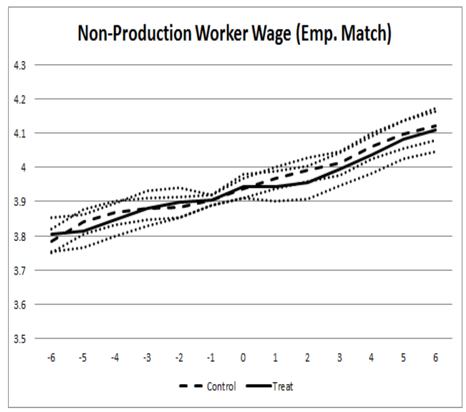
(a) Employment



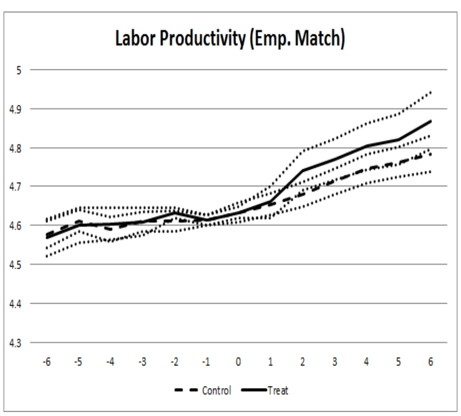
(b) Output



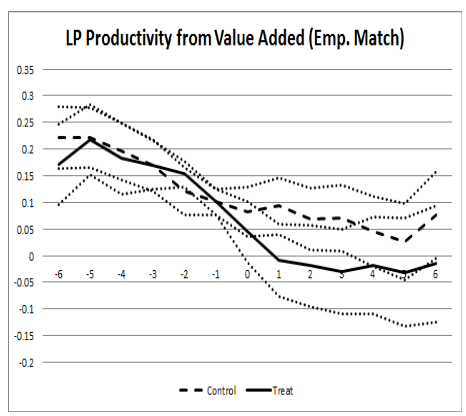
(c) Production-Worker Wage



(d) Non-production Worker Wage

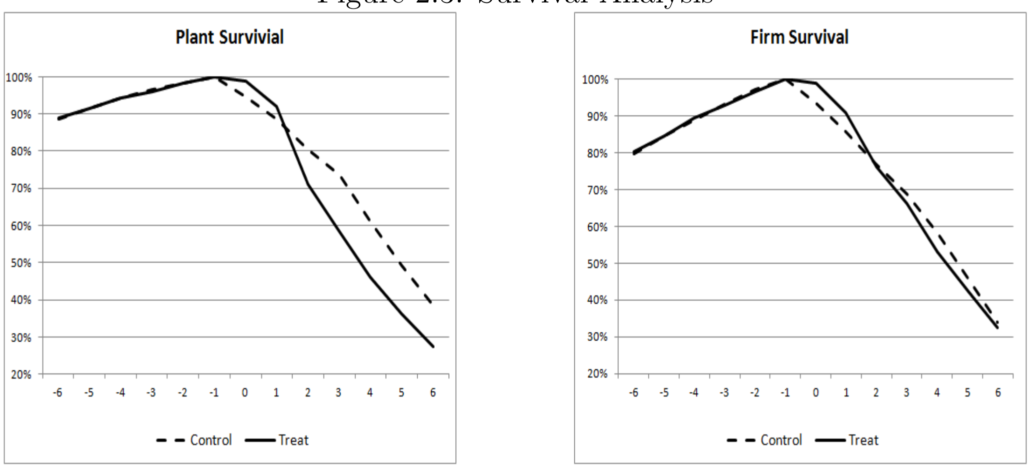


(e) Output per Worker



(f) TFP Levpet

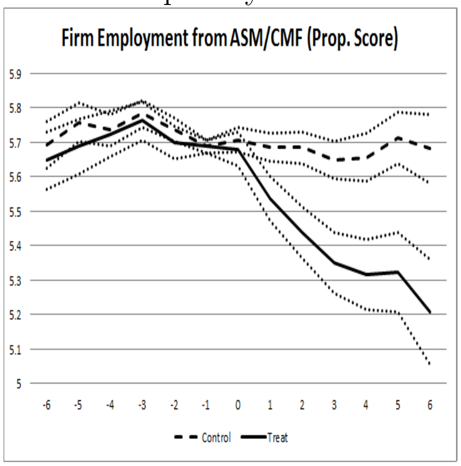
Figure 2.3: Survival Analysis



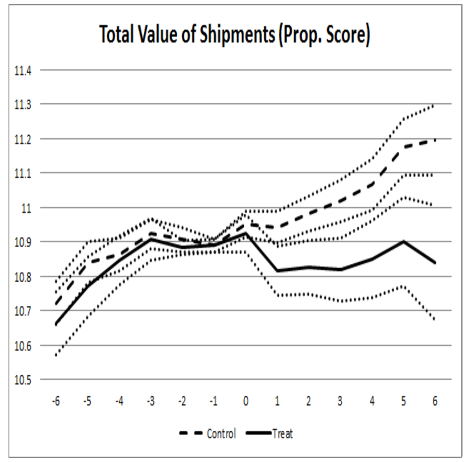
(a) Plants

(b) Firms

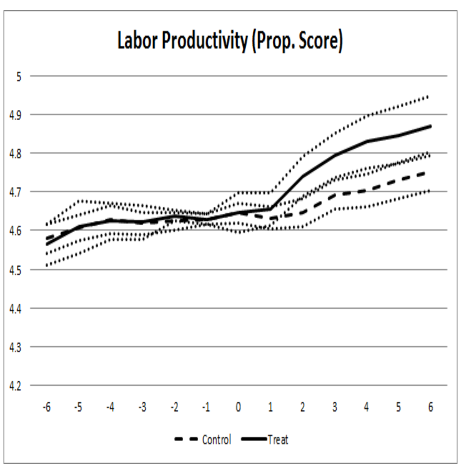
Figure 2.4: Propensity Score Matched Difference-in-differences Estimation Results



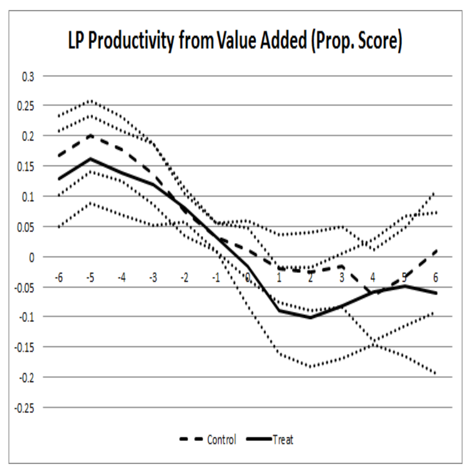
(a) Employment



(b) Output

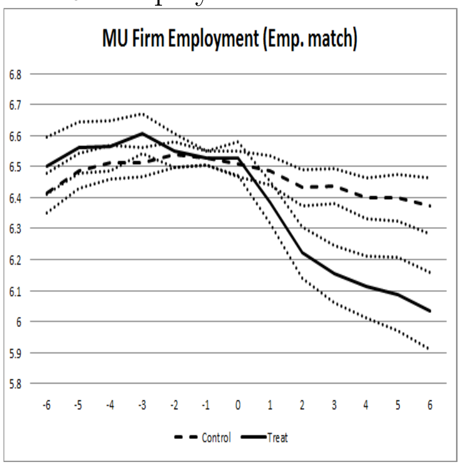


(c) Labor Productivity

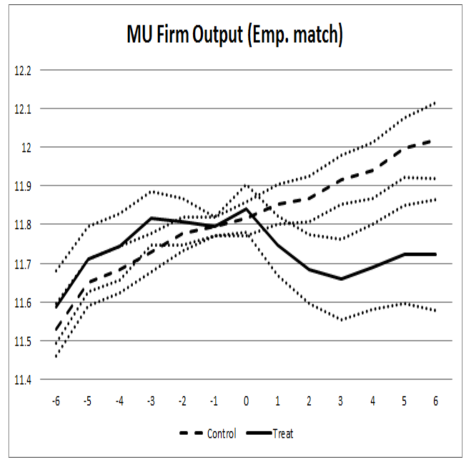


(d) TFP Levpet

Figure 2.5: Employment-Matched DID Estimation Results: Multi-Unit Firms Only

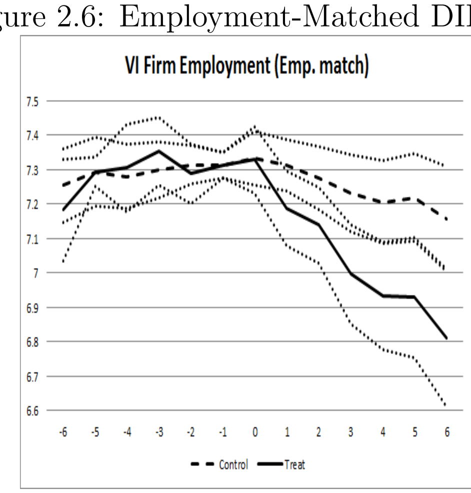


(a) Employment Results

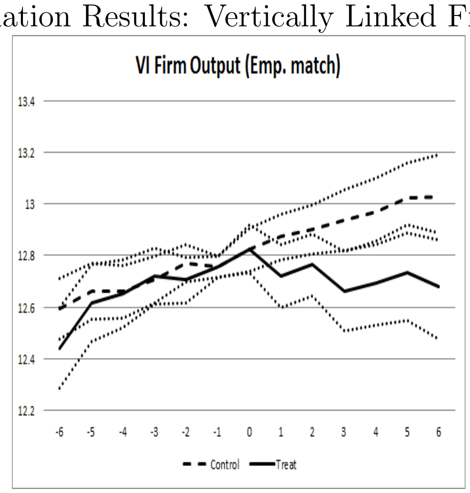


(b) Output Results

Figure 2.6: Employment-Matched DID Estimation Results: Vertically Linked Firms



(a) Employment Results



(b) Output Results

CHAPTER III

Learning and the Value of Relationships in International Trade

(Joint Work with Tim Schmidt-Eisenlohr)

3.1 Introduction

The manner in which relationships evolve between firms in different countries can have major implications for international trade flows. Successful relationships may lead to expansion for firms on both sides, while failed relationships involve disrupted production possibilities in addition to wasted money and effort. In fact, breaking relationships might be so costly for an importing firm that it might choose to remain with an exporting partner even if the particulars of the transaction are not ideal. Recent work (Monarch (2014), Eaton, Eslava, Jinkins, Krizan, Kugler, and Tybout (2014)) has shown that importer-exporter relationships are fairly persistent. But it is not obvious whether this persistence is driven by the acquisition of of positive exporter information, high fixed costs of finding another partner, or simply small cost differences between different potential export partners.

In this paper, we disentangle the different explanations for relationship persistence found among U.S. importers and their foreign export partners. We first utilize confidential U.S. import data and unpack supplier decisions across different imported products to study the effect of learning on relationships. In the empirical section, we document the importance of relationship links between importers and exporters: 48.8% of relationships continue from year-to-year. Additionally, even when switching does occur, 52% of all supplier switching decisions are to "familiar" export partners, meaning importers use partners that were used in small amounts for the same HS10 product previously, or that were used for other HS10 products. Underscoring the importance of familiarity even further is the finding that 43% of such new product purchases also come from export partners used to buy other HS10 products in the past. A key insight of our work is to use variation in the behavior of multi-product importers along these lines to separately identify the process of dynamic learning about a supplier (which occurs across multiple periods and products) from the static search cost explanation.

These stylized facts lead us to put forth a model that incorporates dynamic learning about suppliers, fixed costs of searching for a new supplier, and price differences across suppliers. The framework borrows from the model of exporter learning by Araujo, Mion, and Ornelas (2014), but adds a number of additional features to make it compatible with the empirical findings discussed above. Our setup leads to predictions about how importer decisions to stay or switch, and which supplier to use for both new and existing products. We tabulate these at different levels of aggregation: country level aggregates of switching behavior, firm level decisions, and firm-product level decisions. Switching arises endogenously in the model, due to learning occurring over multiple periods. This implies the lowest cost producer is not always used, even with perfect information about the price of the traded product. In the final section, we present evidence for the additional predictions implied by the model regarding the relationship between institutional quality and switching, as well as the link between the total number of suppliers used and the probability of switching.

Previous work on the topic of dynamic buyer-supplier relationship formation in international trade centers on the study of networks: Rauch (2001) surveys the potential for transnational cultural networks to help smooth international trade and reduce barriers to entry, while Rauch and Watson (2004) present a general equilibrium model through which economic agents can use their supply of networks to either produce/export more efficiently or to become an intermediary. Recent work has made use of the U.S. Customs database used in this paper, which provides information about U.S. importers and their foreign exporting partners. Eaton et. al. (2014) study the relationship between Colombian exporters and the number of U.S. importers they partner with over time and calibrate a search and matching model to match exporter decisions, including sales, number of clients, and transition probabilities. Kamal and Krizan (2012) use U.S. Census trade transaction data to document trends in the formation of importer-exporter relationships. Kamal and Sundaram (2013) use the same U.S. import data to determine how likely textile producers in Bangladeshi cities are to follow other exporters in their same city to export to a particular partner. Other work takes advantage of two-sided trade data to study the effects of heterogeneity on trade: Bernard, Moxnes, and Ulltveit-Moe (2013) develop a model of relationhip-specific fixed costs for exporting using Norwegian buyer-supplier trade data. Our work also fits into the literature on multi-product firms in international trade, including Bernard, Jensen, and Schott (2010) and Bernard, Jensen, and Schott (2011). In this project, we combine a theory of trade network formation, multi-product importers and dynamic learning behavior by importers about the quality of buyers.

The rest of the paper is organized as follows. In Section 3.2, we describe the main features of the importer-exporter database we use. Section 3.3 presents the five broad empirical findings about U.S. importer relationships with foreign partner firms that form the backbone of our project. Section 3.4 describes the model we use that is inspired by the empirical work discussed above, and presents separate predictions that can be tested. Section 3.5 describes the reduced form tests we run to examine these predictions. Section 6 concludes.

3.2 Importer-Exporter Data

The data come from the Longitudinal Foreign Trade and Transaction Database (LFTTD), collected by U.S. Customs and Border Protection and maintained by the U.S. Census Bureau. Every transaction of a U.S. company importing or exporting a product requires the filing of a form with U.S. Customs and Border Protection, and the LFTTD contains the information from each of these forms.[1] There are typically close to 50 million transactions per year. In this paper, we utilize the import data, which includes quantity and value exchanged for each transaction, HS 10 product classification, date of import and export, port information, country of origin, and a code identifying the foreign exporting partner. Known as the *manufacturing ID*, or *MID*, the foreign partner identifier contains limited information on the name, address, and city of the foreign supplier.[2] Monarch (2014) found substantial support for the use of the MID as a reliable, unique identifier, both over time and in cross-section. Kamal and Krizan (2012), Dragusanu (2013), Kamal and Sundaram (2013) and Eaton et. al. (2014) have all used this variable in the context of studying U.S. firm relationships in international trade. This variable allows us to present stylized facts for the role of information in dynamic formation of trade relationships. We present results for relationships between U.S. importers and foreign firms over the years 2002-2008.

We also follow the related literature in our methods for cleaning the LFTTD, using methods outlined in Bernard, Jensen, and Schott (2009) and Pierce and Schott (2009). As in Bernard, Jensen and Schott (2009), we drop all transactions with imputed quantities or values (which are typically very low-value transactions) or converted quantities or values. We also eliminate all related-party transactions, as exporters who are importing from separate branches of the same firm will likely have

[1] Approximately 80-85% of these customs forms are filled out electronically (Krizan 2012).

[2] Specifically, the MID contains the first three letters of the producer's city, six characters taken from the producer's name, up to four numeric characters taken from its address, and the ISO2 code for the country of origin.

very different relationship dynamics than arm's-length exporters. We also concord HS codes over time according to the methodology in Pierce and Schott (2009), which accounts for the changes in HS10 product definitions over this time period.[3]

3.3 Empirical Findings

Our knowledge of relationships between sellers and buyers in international trade is still limited. In this section we illustrate several new empirical findings that shed light on relationship trends between importers and exporters. We start by illustrating the importance of multi-product importers.

Basic facts about multi-product importers 66.1 % of U.S. importing firms import more than one product, accounting for 98.3% of U.S. imports. Figure 3.1 plots the kernel density of the number of products imported, underscoring the significant variation in the number of products imported. The graph underscores that there is significant variation among firms along this domension. The mean number of imported products is 7.67 and the median is 3. 10% of firms in the data import more than sixteen HS10 products.

At the same time, many U.S. importers rely on multiple sources for their imports. For U.S. importing firms, the average number of partners is 23.3, and the median is 4. 72.4% of firms have more than one partner. There is also variation in the number of countries a firm is buying from: the median number of countries is 3, and the average is 11.4. It is possible to disaggregate the data to an even finer level by using a *firm-HS10 product combination* as the unit of observation. With this measure, the average number of suppliers for a firm-product purchase is 3 (with a median of 1), and 36.5% of firm-product combinations use more than one supplier. Thus even within a product category, a sizable share of U.S. importers use more than one trading partner.

[3]None of the results in this paper are significantly different if we track HS codes simply using the present-period code, rather than concording over time.

Facts about trade relationships over time How stable are trade relationships over time? How is this related to the number of products, suppliers and source countries a firm has? In the following we show statistics related to these questions that reveal that year-to-year supplier decisions are far from random. Instead, we find high persistence in trade relationships, a trend that is consistent both with substantial fixed costs of searching for a trading partner and with information asymmetries about the reliability of new suppliers.

We begin by looking at the probability that an importing firm keeps buying a product from the same main supplier year to year. Define a U.S. firm as "staying" with a supplier if it obtains the largest share of its purchases of a product from the same firm for two consecutive years.[4] It is critical to note that this definition of staying is *firm-HS10 product* specific- i.e. one firm with many export products could have multiple stay/switch decisions within one period. Additionally, a firm could buy a product only in one year and that firm-product observation would not enter into this data of relationship dynamics.[5]

According to this definition, 48.8% of U.S. importers stay with the same partner from one year to the next. This is a much higher share than what we should find if trading partners were basically indifferent between different product suppliers after having purchased from one: the median number of exporters in an HS code in one year is 40, meaning that if each year's decision was made randomly, there would a 1 in 40 chance of using the same partner. The size of the exporter choice set plays a role: the share of importers staying is negatively correlated with the number of available exporters selling the same HS10 product. The more partners there are to choose from, the less firms stay with a trading partner.

We now look at the same statistic, taking into account the heterogeneity of firms

[4]The average share of trade from this "major partner" used by a U.S. firm-product combination is 85%, with a median of 100%.

[5]We study new product purchasing decisions later in this section.

with respect to the number of products they are importing. We have shown above that U.S. importers typically import more than one product- in this dimension, U.S. importers remain with their partner on 55.5% of the total number of products they import. Figure 3.2 plots the share of products on which U.S. importers remained with their partner, demonstrating the significant variation among firms. For example, U.S. firms importing two products remain with their partner on 56% of their products. Firms importing 30 products stay with the same partner on 49.2% of their products, and the largest firms remain with exporting partners on 39.9% of their products. In sum, the more products a firm imports, the more the products it switches sellers.

Familiarity with a Partner and Switching Behavior As described above, slightly over half of U.S. import relationships involve new exporter partners from one year to the next. Who are the new partners that U.S. importers buy from? Is the new source completely unknown to the buyer or is there some experience from previous interactions? It turns out that the latter is more common. That is, even when switching, importers tend to buy from firms they are familiar with.

There are two ways in which an importing firm can be "familiar" with a supplier of a given HS10 product in our data, other than it being her current main source. First, the importer can know about another supplier through her purchase of a different HS10 product from that firm in a previous year. Second, the importer can know about a supplier because she previously bought a minority share of the same HS10 product from that source. We examine each of these different avenues below.

Both types of familiarity turn out to be important. We find that 26.6% of all partner switches (again defined as a U.S. firm-HS10 product combination buying from a new partner) are to a supplier that a U.S. importer has bought a different HS10 product from. An additional 25.9% of switching is to partners that were used in the minority for the same HS 10 product. Thus over half of all partner switching is to what can broadly be called "familiar" partners. Furthermore, if we eliminate those cases where each type of familiar switch is impossible, i.e. excluding one-product importing firms from the first definition, and excluding firms that only used a single partner for an HS 10 product from the second definition, the share of switching to familiar partners rises to 69.9%. This constitutes robust evidence that familiarity with a supplier is central to the buying decisions of an importer.

New Product Purchases Familiarity could also matter for the purchase of "new" HS10 products. Define a new purchase of an HS10 product as a U.S. importer buying an HS10 product that it had not purchased in the previous year. 72.2% of importing firms buy at least one new product each year. Again, we find familiarity to be a key explanatory factor in these purchases: 43.9% of new products come from partners used one year previously for a different HS10 product.

We also observe in the data that newly formed relationships- i.e. new importer-exporter observations in any year- start slower, and expand faster if they survive. The top panel of Table 3.1 illustrates that brand new relationships in 2003 tended to have 1.6 products, compared to an average of 2.7 products for relationships that were preexisting. The number of products ramps up quickly for those surviving relationships over time. The same trend is observed in terms of total trade volume from new relationships, with new relationships involving less imports than existing relationships, and growing quickly over time.

To summarize, there are a number of key results from the data that the dynamic model of import sourcing we work with should match:

1. Importing firms have multiple export partners, even for the same HS10 product.

2. Importers have strong links to their chosen export partners over time.

3. Exporter choice is heavily influenced by prior experience with that partner, both within and across products.

4. New relationships start small, and grow faster upon survival.

5. New product purchases are governed in part by exporter usage in other products.

Potential Explanations and Mechanisms for our Findings Why do firms stay with the same trading partner over time? Why is persistence of relationships smaller for firms buying a larger number of products?

There are several explanations for why U.S. importers may choose to stay with the same partner over time. These include avoiding the cost of searching for a new partner, favorable pricing terms, the gains from experience of a long-standing supplier with respect to the customization of the product to the specific needs of the importer and importantly, learning. The last includes learning by the importer about the quality and reliability of the supplier, as well as learning by the supplier about the trustworthiness of the importer. While none of these mechanisms besides the price are directly observable, we can use our rich data to differentiate between them based on their differential predictions for the dynamics and patterns of trade flows over time and across products. A key dimension that we exploit in this paper to disentangle information effects from other factor is the fact that many firms buy multiple products.

3.4 Model Framework

In the following we outline a model that helps explain the empirical patterns we uncovered so far. The goal is to quantify the value of a trade relationship and to think about the welfare consequences of the destruction of trade relationships.

The model builds heavily on work by Araujo, Mion, and Ornelas (2014). While their analysis focused on the problem of an exporter, we use their framework to study the related decisions of an importer. We follow their basic setup closely before extending it to allow for multi-product firms as well as for differences in production costs.

Basic Setup We begin by describing the problem of a single buyer matched to a single supplier. Assume that a fraction $\widehat{\theta}$ of suppliers are patient whereas the remainder of them are myopic. As in Araujo, Mion, and Ornelas (2014), we assume that the difference in the discount rates is so large that patient suppliers always want to keep a trade relationship alive whereas myopic firms try to deviate from the contract whenever they get an opportunity to do so. Such an opportunity arises when the source country fails to enforce the contract. This happens with probability $1-\lambda$, where λ is a measure of the quality of legal institutions in the source country.

While in reality, firms choose from a set of different payment contracts, for now, we assume that all transactions are settled cash-in-advance. That is, before goods are delivered, the importer needs to send the agreed amount to the supplier. Only then, the exporter may send the goods.

Buyer Behavior As there are two types of suppliers in the economy, learning plays a central role. Initially, buyers believe correctly that the probability that a seller of a product is patient and will fulfill the contract is equal to the population mean $\widehat{\theta}$. Every period that a relationship survives, they update their beliefs according to Bayes Rule. Remember that a myopic supplier defaults whenever there is an opportunity (probability $(1-\lambda)$). If a buyer has successfully purchased from the same seller for k periods, the posterior probability that the seller is patient can be derived as:

$$\theta_k = \frac{\widehat{\theta}}{\widehat{\theta} + \left(1-\widehat{\theta}\right)\lambda^k} \tag{3.1}$$

Importantly, the probability only depends on the length of time that a buyer has been buying from the same seller. It is easy to see that for large k, θ_k converges to 1, that is the buyer is almost certain that the seller is of the good type.

3.4.1 Single Product Importers

The Static Case In the following, we introduce a fixed cost of keeping a trade relationship from one period to the next. Denoted by f, this cost is paid at the beginning of the period, before the optimal import bundle is chosen. Then, expected importer profit in the current period when buying from a supplier that she traded with for k periods are:

$$\pi_k = \max \ \{(\theta_k + (1-\theta_k)\,\lambda)\, R\,(q) - cq - f, 0\} \tag{3.2}$$

The buyer can sell the goods for revenue R if if they are successfully delivered by the supplier. This happens with probability $\theta_k + (1-\theta_k)\,\lambda$ (that is, if the seller is non-myopic, or if the seller is myopic, but no opportunity to default occurs). We assume that the buyer has all bargaining power, so she pays the seller the marginal cost of production c for each unit purchased q. Finally, the importer has to pay the per period cost of sustaining the trade relationship f. The firm can always decide to cancel the trade relationship and receive profits of zero.

The net present value of future profits Assume that with probability δ a relationship is separated for exogenous reasons, such as supplier exit. Further, assume that this shock takes place between trading periods, so that the Bayesian updating is not affected by this variable. We can then derive the net present value of a given trade relationship as:

$$\Pi = \pi_0 + \sum_{i=1}^{\infty} \left\{ \left(\prod_{j=1}^{i} (1-\delta)[\lambda(1-\theta_j) + \theta_j] \right) \pi_i \right\} \tag{3.3}$$

$(1-\delta)[\lambda(1-\theta_j)+\theta_j]$ is the probability that a relationship active in period $j-1$ survives to period j. $\prod_{j=1}^{i}(1-\delta)[\lambda(1-\theta_j)+\theta_j]$ is therefore the probability that a relationship that is formed in period 1 is still active in period i.

The case of two suppliers Suppose now that there are two suppliers of the same product, each of whom has been used by the importer. To distinguish between them we add a superscript $s \in \{1,2\}$ to the relevant variables. Suppliers can differ in their production cost c^s. Furthermore, the buyer may have different posterior beliefs about their reliability $\{\theta^1_{k_1}, \theta^2_{k_2}\}$. For now, assume that both suppliers come from the same base population and that they face the same enforcement probabilities. That is $\widehat{\theta}^1 = \widehat{\theta}^2$ and $\lambda^1 = \lambda^2$. This implies that differential beliefs about the supplier types can only arise if the importer has been buying from the two firms for a different number of periods, i.e. $k_1 \neq k_2$.

Suppose that the importer has a longer relationship with firm 1, meaning $k_1 > k_2$. It follows directly that $\theta^1 > \theta^2$, i.e. the buyer has a better opinion about seller 1's reliability. Suppose also, that seller 2 has a better technology that allows her to produce the product at a lower production cost $c^2 < c^1$. In this simple case we can make the following prediction:

Prediction III.1. *For sufficiently large δ and fixed q, an importer may buy from a higher cost exporter if she has a longer relationship with that firm than with an alternative lower cost supplier.*

This prediction is quite straightforward. First, denote the likelihood of delivery by $\tilde{\theta}^s = \theta^s + (1-\theta^s)\,\lambda$. Now, consider the limiting case of $\delta \to 1$. Then, the net present value of future profits collapses to the static one-period profits π^s_0. In that case, based on equation (**??**) an importer buys from the higher cost supplier 1 if:

$$\Delta c\ q = (c^1 - c^2)\ q < R(q) \left[\tilde{\theta}^1 - \tilde{\theta}^2\right] \tag{3.4}$$

If production cost differences $\Delta c\ q$ are not too large, the familiarity effect $(\tilde{\theta}^1 > \tilde{\theta}^2)$ dominates and the importer buys from the better known firm.

Searching for Suppliers We now turn to the dynamic aspects of searching for suppliers. As we saw in Prediction **??**, a firm may decide to buy from a higher cost supplier in the short run. However, the importer may decide to try out a new supplier and keep ordering from it for a while to see whether she is reliable.

A challenge in analyzing this question is how much an importer has to order to make the supplier reveal its type. Given the dynamic nature of the relationship, we should expect such a constraint to be related to the maximum growth rate in the ordered quantities over time. More precisely, the discounted present value of future gains from trade has to be dominated by the one period deviation payoff for the myopic suppliers. It is straightforward to see that for sufficiently high discount rates of the myopic firms, this constraint can be arbitrarily weakened. Instead of analyzing this aspect explicitly, in the following, we assume that it is sufficient to order a very small amount of ϵ from the supplier to test its reliability. However, finding a new trading partner is costly. Whenever a firm wants to test a new supplier, it has to pay a fixed cost f_N. This could be a pure search cost. An alternative interpretation would be that this cost captures the fact that firms actually have to order more than ϵ in order to trigger defaults from myopic firms.

The updated single-period profit equation from purchasing from a supplier s is thus:

$$\pi^s = \max_{q \geq \epsilon} \tilde{\theta}^s R(q) - c^s q - f_N \mathbb{1}[s = new] \tag{3.5}$$

There are three key aspects to determining which supplier an importer prefers:

- The dynamic reputation of seller s, $\tilde{\theta}^s$, compared to other sellers s'.
- The cost paid to seller s, c^s, compared to other sellers s'.
- The fixed cost of buying from a seller s if they have not been used before, f_N.

Which suppliers will a firm drop over time and which will it keep? Note that an importer does not automatically drop a new supplier with a higher marginal cost than the current one. If the exogenous shock δ is sufficiently high and the baseline share of patient suppliers sufficiently low, it may well be worth it to have a reserve supplier even if that firm is less efficient. This observation is consistent with Finding 1 from Section 3.3 above that many firms use multiple exporters for their products. It also speaks to the level of persistence in relationships over time from the data:

Prediction III.2. *Relationship persistence between buyers and suppliers can be high, even with price dispersion among export choices.*

While we still need to quantify this prediction and see how much persistence can be generated, to some extent, this is a corollary to Prediction **??**. Trade with low-cost unknown parties may not be profitable. If learning is slow, the exogenous death rate δ is high and there is a substantial cost of trying out a new supplier, it may not be worthwhile to change from a familiar source to a new one. This prediction is consistent with Finding 2 discussed in Section 3.3.

The model can also speak to another fact about switching behavior observed in the data and summarized in Finding 3: when switching suppliers, importers tend to buy from already familiar firms. Consider two suppliers, one with whom the importer had at positive experiences in the past and one who is new and therefore completely unfamiliar. Then, ceteris paribus, given the Bayesian updating, the importer should buy from the familiar exporter rather than the new one. This is captured in the next prediction:

Prediction III.3. *Switching is likely to occur to partners that are already known through prior purchases.*

Finally, we can match the empirical result in Finding 4, concerning the growth patterns of new relationships.

Prediction III.4. *New relationships are likely to start small, then grow faster, compared to preexisting relationships.*

This prediction is the same as in Araujo, Mion, and Ornelas (2014), in their case for exporters learning about importers. There are two potential explanations. First, following the logic in Araujo, Mion, and Ornelas (2014), the importer may choose optimal quantities based on her belief about a specific exporter. This leads to an increasing path of purchases over time. Alternatively, the importer may keep buying from a familiar source while buying small amounts from a new firm until enough information has been gathered. A theoretical challenge in the second approach is how to pin down how much an importer needs to order from a supplier to generate learning. Above, we simply assume some ϵ quantity is necessary in order to start or maintain the learning process. That is, we abstract away from optimal import share calculations on behalf of the buyer.

Separately from our findings discussed above, the simple model discussed here lends itself to two additional tests. It is informative to consider a case where the quality of legal institutions λ can vary by country. As can be seen from equation (**??**), the speed of learning decreases in the strength of contract enforcement. This is quite intuitive. Myopic suppliers can only deviate when contract enforcement fails, which happens more often in countries with bad legal institutions. We should therefore expect firms importing from exporting countries with better institutions to have more persistent relationships and to switch less.

Prediction III.5. *The share of firms switching should be lower in countries with better institutions.*

This prediction is also a byproduct of the model designed in Araujo, Mion, and Ornelas (2014), though they do not have dual-sided firm data in order to calculate the share of switching.

Secondly, the model implies that the more partners an importer uses overall, the more likely a switch becomes. We have shown this to be the case in the simple case with two suppliers, whereby switching is more likely if the importer has ongoing relationships with each supplier.

Prediction III.6. *The more partners used by an importer, the more likely they are to switch to a different partner for that product. Additionally, they are more likely to switch to one of those partners that were used before.*

There are two potential explanations for this result: increasing returns to scale of searching may allow larger firms to build up relationships more cheaply. Alternatively, the larger number of current suppliers may give an importer more firms to switch to that she is already familiar with.

We go on to test these predictions formally in Section 3.5.

3.4.2 Multi-Product Importers

We next consider multi-product importers. Let us go back to the case of buying from a single supplier. When would an importer buy multiple products from the same firm? To study this problem, we follow the multi-product firm literature by assuming that every producer has a core product. Adding additional products moves the firm away from its core competency and therefore increases production costs. Assume therefore that additional products have higher marginal costs by factor $\gamma > 1$. Further, assume that learning about a supplier's type happens at the firm and not at the product level. Therefore, buying multiple products does not increase the speed of learning. Assume also that now there is an additional fixed cost f_p that has to be paid per product bought. Under these assumptions, it is straightforward to calculate profits from buying product n of a supplier as: Profits from product n are thus:

$$\pi_s(n) = (\theta_k + \lambda(1 - \theta_k))\, R(q) - c\gamma^n q - f_p \tag{3.6}$$

Product $n > 1$ is bought whenever the current profit term is greater than 0. This can be solved for.

$$\theta_k > \frac{1}{1-\lambda}\left[\frac{c\gamma^n q + f_p}{R(q)} - \lambda\right] \tag{3.7}$$

We can also solve equation (**??**) for the number of products sold. This delivers:

$$n = \frac{\ln\left[\tilde{\theta}_k R(q) - f_p/cq\right]}{\ln\gamma} \tag{3.8}$$

Prediction III.7. *The more familiar an importer is with a supplier, the more products she buys from that firm ($\partial n/\partial\theta > 0$).*

This is consistent with Finding 5 discussed in Section 3.3 above: namely, new product decisions are highly correlated with whether an importer has experience with that exporter. We also present two additional conjectures from the theory that we go on to test in Section 5:

Conjecture 1: The better the institutions of the exporting country, the higher the share of switching to exporters of of that country familiar from other products.

Conjecture 2: The more partners used by an importer across all products, the more likely that importer is to switch partners. They are also more likely to switch to an exporter used by one of their multiple products.

3.4.3 Simulations

In this subsection, we demonstrate some of the features of the model with a numerical example. Specifically, we solve the model under CES demand for the final good, and simulate trajectories for profits, prices, and other key variables in the model.

As above, expected importer profits from using any seller s at time t are:

$$\pi_t^s = \left(\theta_k^s + \left(1 - \theta_k^s\right)\lambda\right) R\left(q\right) - c^s q - f$$

where k is the number of periods that the buyer has been buying from supplier s by time t.

We again use $\widetilde{\theta}^s = \left(\theta_k^s + \left(1 - \theta_k^s\right)\lambda\right)$ to save notation. Analysis of the problem while allowing for CES demand ($q = A\left(p^s\right)^{-\sigma}$) for the final good of the producer is straightforward. Assume there are two potential sellers to choose from, with costs to the buyer c_1 and c_2. The optimal price depends on which supplier s is used:

$$p_t^s = \frac{\sigma}{\sigma - 1}\frac{1}{\widetilde{\theta}^s}c^s$$

This means that revenue from supplier s at time t is $R^s t = A\left(p_t^s\right)^{1-\sigma}$, and profits are:

$$\pi_t^s = \frac{1}{\sigma}A\left[\frac{\sigma}{\sigma - 1}\frac{1}{\widetilde{\theta}^s}c^s\right]^{1-\sigma} - f \tag{3.9}$$

The buyer is comparing profits from using either seller. Note that without information $\widetilde{\theta}$ in the model, profits are maximized by simply using the buyer with least cost. However, by allowing for dynamic adjustment of partners, we can endogenize the decision to switch partners, whereby an importer might first prefer to use a buyer of higher cost that it has better information about, switching only once it learns enough about the other buyer to be sure they will not default.

Setting $\lambda = 0.6$, the share of good sellers $\widehat{\theta}$=0.6, costs $\{c^1, c^2\} = \{1, 1.2\}$, and $k_2 = k_1 + 3$, we can obtain the graphs found in Figure 3.3.

In Panel A, the solid line represents the supplier with high cost that possesses a better reputation, by virtue of the fact that $\widetilde{\theta}$ is higher. This is because the high-cost supplier has been used for longer. Panels B and C show that eventually, as information improves about the low cost seller, the buyer can charge lower prices for the final good, increasing revenue at a faster pace. Indeed, panel D demonstrates that by period 7, the reputation of the low cost seller improves enough such that there are higher profits from utilizing that seller, thereby inducing dynamic switching behavior.

Furthermore, we can justify the purchases of more products from a seller using our framework of multi-product importers. Again as before, we have the profits from individual product n from seller s as

$$\pi^s(n) = (\theta_k + \lambda(1 - \theta_k))\, R(q) - c\gamma^n q - f_p$$

with products only being bought that satisfy the condition in Equation (3.7). We set the marginal cost of an extra product at $\gamma = 1.02$. Figure 3.4 demonstrates the evolution of the number of products purchased over time, again with the more expensive seller initially selling more products to the buyer, up until the reputation of the cheaper seller improves enough.

3.5 Results

In this section, we describe the tests we undertake for Predictions III.5 and III.6 and Conjectures 1 and 2 from above, using the LFTTD data described in Section 3.2.

First, we test whether source countries with better institutions tend to have a higher share of maintained relationships over time. Guided by Prediction III.5, our estimating equation is:

$$ShareStay_c = \alpha + \beta_1 \lambda_c + \beta_2 PCGDP_c + \nu_c \tag{3.10}$$

Based on Prediction III.5, we would expect a greater fraction of U.S. import relationships to persist in countries with better legal institutions λ, due to better enforcement of contracts and the low rate of learning that takes place in sources with better institutional quality. The variable $ShareStay$ is the fraction of importer-exporter relationships that are maintained between the U.S. and from country c averaged over all the years of our sampling frame, while $PCGDP$ is log per capita GDP in country c. We also include private credit coverage as an additional regressor. To measure the quality of institutions λ, we use a collection of institutional quality variables taken from the World Bank World Development Indicators. First is the Strength of Legal Rights index, which measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders in a country. Since this variable is not directly a measure of contracting rights,we also include both the number of procedures required to enforce a contract, and the ordinal ranking of countries by such a procedure. Neither of these two institutional quality variables has significant changes over our sample period from 2002-2008, so we simply use 2004 values for each, as well as for per-capita GDP, while averaging the ratio of staying partners for each country over time.[6] As can be seen in the top part of Table 3.2, the results are consistent with the predictions of the model: higher legal rights and fewer procedures in exporting are both indicative of a larger share of firms remaining with their partner over time.

In line with Conjecture 1, we run the same specification replacing the dependent variable with the share of firms that obtain new products from familiar exporters at country level. This variable is the fraction of all new products coming from a certain country that arrive from familiar partners. From the bottom panel of Table 3.2, we see again that better institutions lead to a greater share of new products being sourced from familiar partners.

It is also possible to test the extent to which switching is linked to the number of partners used, as in Prediction III.6 and Conjecture 2. There are two avenues through which familiarity might be an important determinant of the decision. First, an exporter could be familiar as a minority partner for the same product. To explore this channel, we test whether having more partners within a firm-HS10 product code combination is correlated with whether a minority-to-majority switch occurs. We also include total size of imports in each firm-product combination as a regressor. The results in Table 3.3 confirms Prediction III.6- having more partners for a product indeed means importers are more likely to switch. The second avenue for familiarity is buying a product from an export partner previously used for some other product. Here, we test whether a switch came from a familiar firm against the total number of partners used by a firm (rather than a firm-HS10 product combination). Table 3.4 confirms that these types of switches are indeed more likely to occur among firms that have more overall firm partners. As above, firms with more overall partners are more likely to switch. However, including either by including total firm imports directly or splitting firms into size deciles, we see that given the same number of partners, larger-volume importers are actually more likely to remain with their partner over

[6]The results are the same if we use yearly measures of *ShareStay* for each country c with individual year observations of $PCGDP$ and $lambda$.

time.

3.6 Conclusion

We have presented evidence demonstrating that familiarity is critically important to U.S. importers in making supplier decisions. When deciding from whom to buy, not only are importers likely to continue buying from the same partner over time, but even when switching, they use information from their individual experience with exporters. We demonstrate that both buying a small amount from an exporter, and buying different products from an exporter are strongly related to the decision of whom to buy from. New products are also extremely likely to be bought from exporters that were used previously. Guided by these regularities and recent work on institutions, we have implemented a model of learning in international trade that delivers predictions about how importers match with exporters in international trade that are consistent with patterns in the data. Future work can take the simple model we have developed here, and estimate the key components of the model directly, with the goal of calculating the effect of trade volumes and welfare as a result of preexisting relationships between importers and exporters.

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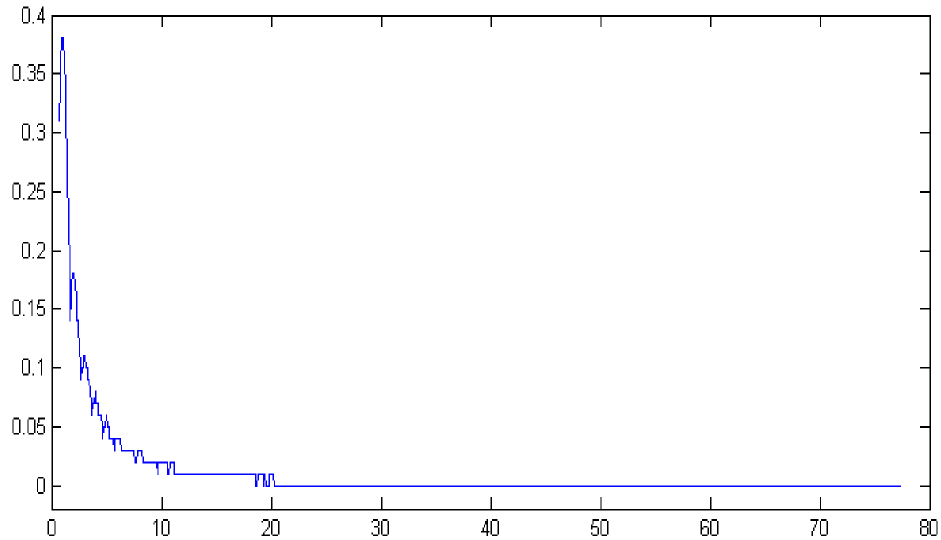
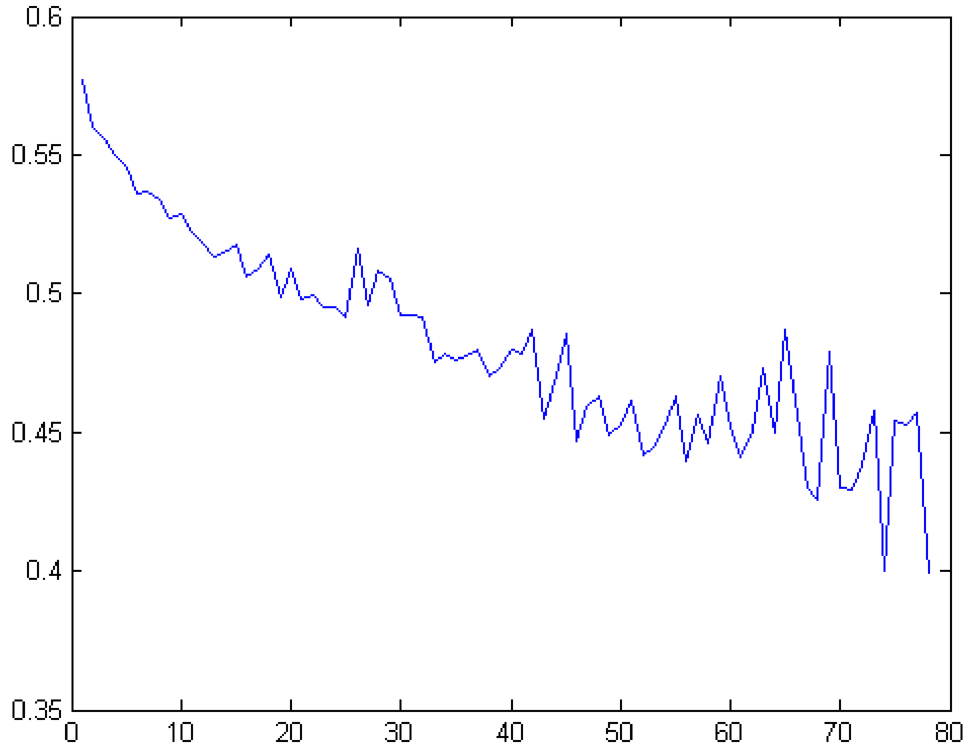
Figure 3.1: Kernel Density, Number of Imported Products



Notes: The graph shows the density of U.S. firms for each number of total HS 10 products imported. Product codes are taken from customs declarations by U.S. importers, and adjusted using the methodology described in Pierce and Schott (2009). The density is cut off for readability above 78 products, accounting for 99% of the total sample. The kernel density is computed using 1000 grid points within this range. 10% of U.S. importing firms import more than 16 HS 10 products.

Figure 3.2: Share of Products "Staying" with Same Partner, by Number of Products



Notes: The graph shows the share of products in which a U.S. importing firm has kept the same partner over a two year period, over the total number of products imported continously over those two years. For example, the first point demonstrates that among U.S. firms importing two products, the average share of those two products in which the same partner is used is about 57%. The highest-scale importers tend to remain with their partner on a smaller share of products, bottoming out at approximately 40%. For disclosure reasons, the sample is cut off at 78 products.

Table 3.1: New Relationships in 2003, versus Existing Relationships from 2003

Average Number of Products

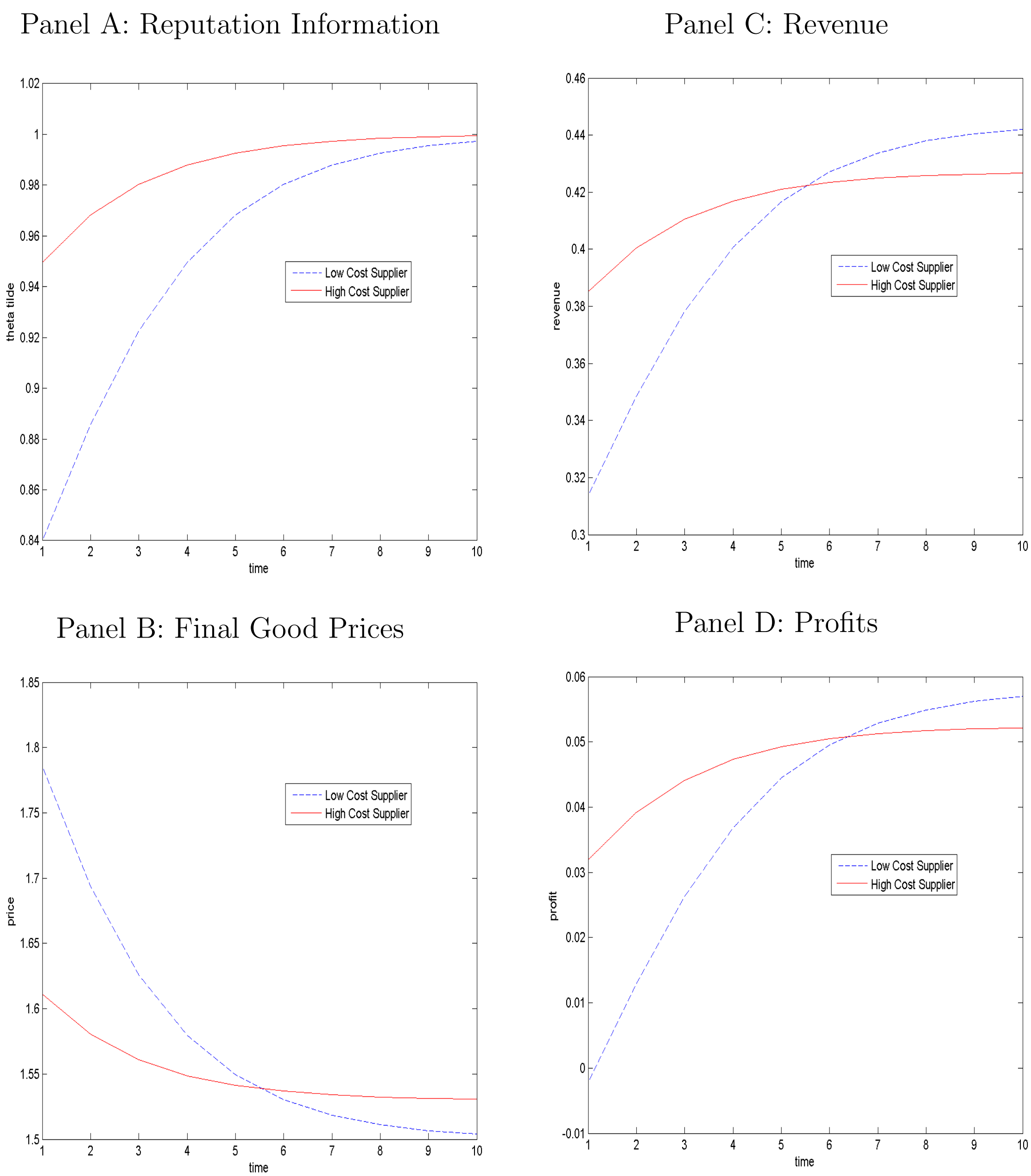
	2003	2004	2005	2006
New Relationships	1.6	2.4	2.8	3
Existing Relationships	2.7	3.2	3.5	3.6

Average Value of Imports (Log)

	2003	2004	2005	2006
New Relationships	9.72	10.71	11.05	11.2
Existing Relationships	10.92	11.31	11.5	11.57

Notes: This is a comparison of the size of trade for new importer-exporter relationships formed in 2003 to trade occurring in existing relationships in 2003. The top panel is the number of products imported by relationships between U.S. importing firms and foreign exporters, while the bottom panel is the total value of trade. For the year 2003, 61.3% of total firm-firm relationships are new.

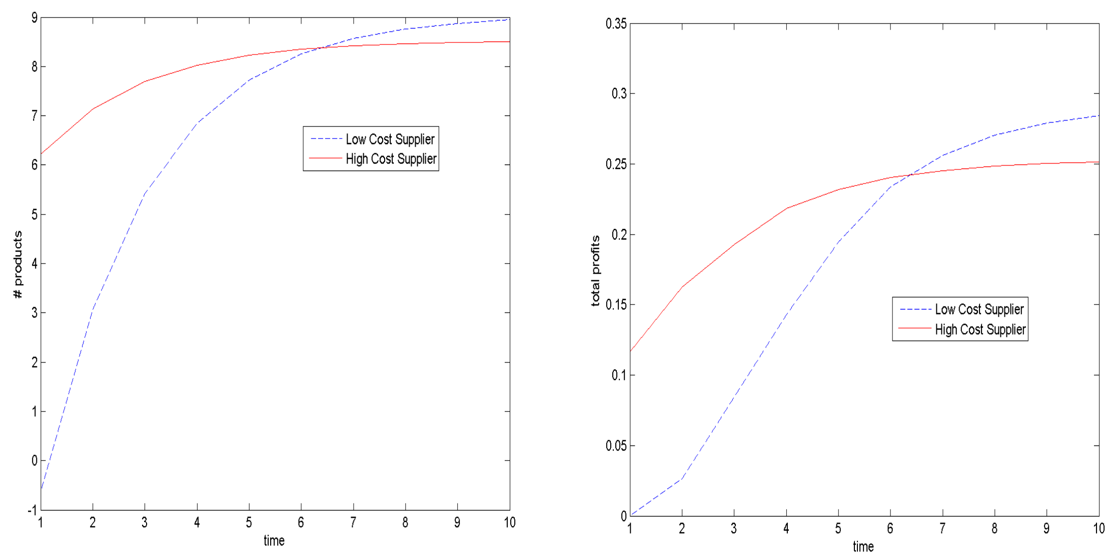
Figure 3.3: Model Simulations- Single Product Importers



Notes: These simulations are for single product importers facing CES demand and having profits according to Equation (3.9) in Section 4.3. The choice is which supplier to use, a high-cost seller with a better starting reputation (solid line) or a low-cost seller with a less reputation (dotted line).

Figure 3.4: Model Simulations- Multiple Product Importers

Panel A: Number of Products Panel B: Total Profits, All Products



Notes: These simulations are for multiple product importers facing CES demand and having profits according to Equation (3.9) in Section 4.3. The choice is which supplier to use, a high-cost seller with a better starting reputation (solid line) or a low-cost seller with a lesser reputation (dotted line), as well as how many products to buy from each.

Table 3.2: Relationship between Institutions and Staying/ Switching Decisions

Dep. Variable: Share of Importers Staying with Exporter Year-to-Year, 2002-2008

	(1)	(2)	(3)
Log Strength of Legal Rights	0.0489**		
	(0.02253)		
Procedures to Enforce a Contract		-0.00673***	
		(0.00195)	
Rank (Procedures)			-0.00106***
			(0.00027)
Log Per Capita GDP	0.02403***	0.01893***	0.01677**
	(0.00740)	(0.00743)	(0.00747)
Constant	0.16496**	0.52975**	0.37517***
	(0.05531)	(0.11278)	(0.07171)
N	151	152	152
R^2	0.14	0.18	0.20

Dep. Variable: Share of Switches To Exporters Used for other Products, 2002-2008

	(4)	(5)	(6)
Log Strength of Legal Rights	0.06471**		
	(0.02438)		
Procedures to Enforce a Contract		-0.00539**	
		(0.00217)	
Rank (Procedures)			-0.00078**
			(0.00031)
Log Per Capita GDP	0.0264***	0.02458***	0.0237***
	(0.00808)	(0.00836)	(0.00846)
Constant	-0.01302	0.32657**	0.19129**
	(0.06102)	(0.12559)	(0.08084)
N	149	150	150
R^2	0.16	0.16	0.16

Notes: The independent variables come from the World Bank's World Development Indicators. Strength of Legal Rights is an index from 0 to 10, and measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders in a country. Number of procedures to enforce a contract are the number of independent actions, mandated by law or courts, that demand interaction between the parties of a contract or between them and the judge or court officer. Per Capita GDP and Private Credit Coverage variables are also from the World Bank. Three asterisks implies significance at 1%, two asterisks implies significance at 5%.

Table 3.3: Staying/Switching Decisions, using Firm-Product Characteristics

	Stay	Stay	Switch to Minority	Switch to Minority
	(1)	(2)	(3)	(4)
Total Partners	-0.00388***		0.00163***	
	(0.00014)		(0.00001)	
Log Total Partners		-0.19332***		0.15586***
		(0.00132)		(0.00169)
Log Importer Size	0.02119***	0.06504***	0.08044***	0.03624***
	(0.00044)	(0.00055)	(0.00081)	(0.00054)
Constant	0.26771***	-0.7735***	-0.60280***	-0.26456***
	(0.00467)	(0.00568)	(0.00857)	(0.00621)
Year Fixed Effects	Yes	Yes	Yes	Yes
N	3,108,201	3,108,201	1,592,852	1,592,852
R^2	0.06	0.11	0.17	0.23

Notes: Three asterisks implies significance at 1%, two asterisks implies significance at 5%.

Table 3.4: Staying/Switching Decisions, using Firm Characteristics

	Stay	Stay	Switch to Exporter from Other Product
	(1)	(2)	(3)
Log Firm Total Partners	-0.07676***	-0.05576***	0.01910***
	(0.00074)	(0.00045)	(0.00057)
Log Importer Firm Size	0.02870***		0.00017
	(0.00062)		(0.00055)
Firm Size Deciles			
2		0.02097***	
		(0.00513)	
3		0.03723***	
		(0.00558)	
4		0.04520***	
		(0.00518)	
5		0.05996***	
		(0.00550)	
6		0.07523***	
		(0.00556)	
7		0.08581***	
		(0.00601)	
8		0.10629***	
		(0.00628)	
9		0.12123***	
		(0.00665)	
10		0.15504***	
		(0.00691)	
Constant	0.37481***	0.17077***	0.59676***
	(0.00709)	(0.00615)	(0.00665)
Year Fixed Effects	Yes	Yes	Yes
N	3,108,201	3,108,201	1,592,852
R^2	0.06	0.11	0.17

Notes: Three asterisks implies significance at 1%, two asterisks implies significance at 5%.

APPENDICES

APPENDIX 1.A

Robustness and External Validity of the MID

At this point, I describe the foreign exporter identifier in more detail. As shown in Figure 1.A, two characters on the country of the manufacturer, six characters related to the name of the manufacturer, four characters (in certain circumstances) related to the address of the manufacturer, and three characters related to the city of the manufacturer make up the exporter identification variable. The MID is assembled by the U.S. importing firm (or more likely, by a specialty customs broker utilized by the importing firm) according to an exhaustive list of regulations found in the instructions to the baseline U.S. Customs Document CBP Form 7501, along with the other particulars of the import transaction[1]. I use this identifier to study the behavior of U.S. importers over time, namely what exporter they choose, where the exporting firm is located, and what guides the decision for what partner U.S. importers will choose in the future.

Clearly, the reliability of this variable is important for the stylized facts laid out above. I therefore first present some background on how the U.S. government encourages honest construction of this variable. According to the U.S. Customs and Border Protection, over 99% of entry summary transactions are filed electronically, reducing the risk of misread or misspelled codes. As mentioned above, these forms are also overwhelmingly filed by professional customs brokers well aware of the rules for constructing these codes. Another concern is that the code does not capture the actual producer of a good, but rather some "middle-man", the use of which are very common among firms importing from China (Tang and Zhang 2012). Importantly, even if a U.S. importer makes use of an intermediary to help them find an exporting firm, information about the actual source of the product is carried through on the final invoice through the entire process[2]. It should also be noted that importers are explicitly warned by the U.S. CBP to make sure that the MID they assemble is reflective of the true producer of the good, not any type of intermediary or processing firm:

[1]See CBP Form 7501 Instructions, p. 30-32 for the exact details.

[2]Krizan (2012), p.10-11, makes clear that this information is available at all stages of the trade transaction.

"Trading companies, sellers other than manufacturers, etc. cannot be used to create MIDs. Entries and entry summaries in which the first two characters of the MID do not meet the country of origin ISO code, or are created from a company that is known to be a trading house or agent and not a manufacturer, will be rejected for failure to properly construct a MID...Repetitive errors in the construction of MIDs for entries of textile or apparel products will result in the assessment of broker and importer penalties for failure to exercise reasonable care." — U.S. Customs and Border Protection

I augment these facts with a number of checks on this variable by utilizing a rich panel dataset on Chinese firms. This comprehensive dataset from China's National Bureau of Statistics covers all state-owned enterprises (SOEs) and non-SOEs whose annual sales are more than five million *renminbi*, and includes more than 100 financial variables listed in the main accounting sheets of firms.[3]. Industries are classified according to the China Industry Code (CIC). Sadly, due to confidentiality and security concerns, the datasets cannot be merged at the firm-to-firm level at this time, despite the availability of plausibly consistent identifiers in both datasets related to name and address. However, this dataset has many other uses in the context of studying importer-exporter behavior.

One application where the NBS industrial database is useful is I can follow the rules laid out for how to construct Manufacturer IDs and assess how commonly multiple firms in an industry possess the same MID- a type of outside check on the uniqueness of the foreign exporter identifier. I do this for five industries in 2005, with uniqueness statistics illustrated in Table 1.A Panel A. Although this analysis is subject to some qualification- namely, the NBS data is not the entire universe of Chinese firms, nor is there any gurantee that the name of the firm in Chinese characters (as in the NBS data) is the same as the romanized version of the name of the firm- it appears that the MID does a good job of uniquely identifying foreign firms at the industry level.

An additional complication for studying geographic switching behavior is that only three letters of the city are given in the MID. For example, a city code of "SHE" would be assigned to both Shenyang and Shenzhen, both major cities of more than 8 million people. Again, I use the China Industrial Database in 2005 to check how widespread the problem would be in particular industries. Table 1.A Panel B shows that such cases do indeed occur, but not with fatal frequency. It should be noted too that the figures on city-switching from Table 1 will only be misspecified if a U.S. importer switches from a city to another city that happens to start with the same first three letters.

A final concern raised by the construction of the MID is that an importing firm may in fact choose to stay with a supplier, but if the supplier changes its name or address, a new MID means that I will classify that importer as a switching firm. The China Industrial Database tracks firms over time with a unique firm identifier, so I can collapse the data into a panel and see how many firms would fall into this

[3]For more information on this database, see Feenstra, Li, and Yu (2011).

hypothetical scenario by having a change in name or address from 2005 to 2006 that changes their MID. The results of this test are in Table 1.A Panel C. Again, though such situations do happen, the vast majority of Chinese exporting firms in the NBS data do not have undergo such a change.

APPENDIX 1.B

Robustness Checks for the Stylized Facts

In Section 1.2, I demonstrated that among U.S. continuing importers from China, partner switching is pervasive, there is a strong geographic component to the switching decision, and that these two trends become more pronounced over time. My baseline specification is to define a "switch" as a U.S. importing having a completely different set of partners for a product from one year to the next. Below I lay out a number of other specifications.

Figure 1.B.1 shows that the same stylized facts carry through even when using an alternate of switching: defining an importer as "staying" if it stayed with at least one or more of its partners: importer-exporter relationships are highly volatile, and geography matters a great deal in the switching decision. The same results come through if I analyze only U.S. manufacturing firms (as identified in the 2002 Census of Manufacturers) as in Figure 1.B.2, or if I use firm-HS6 product as the unit of analysis, as shown in Figure 1.B.3. Figure 1.B.4 presents the individual years that make up the switching data in Figure 1.1. Ultimately, it is clear that the stylized facts described above are consistent across a variety of different specifications.

I also check the estimation of Equation (1.1) using data from 2005-2006. As can be seen in Tables 1.B.1 and 1.B.2, there is still a strong correlation between high prices and the decision to switch, with those importers paying the highest price close to 4% more likely to switch than the omitted decile of prices.

APPENDIX 1.C

Proof of Proposition 1

Assumption 1. (Conditional Indepdendence) *The joint transition density of p_t and ϵ_t can be decomposed as:*

$$h\left(p_{t+1}, \epsilon_{t+1} | p_t, x_t, x_{t+1}, \epsilon_t\right) = g\left(\epsilon_{t+1}\right) f\left(p_{t+1} | p_t, x_t, x_{t+1}\right)$$

I also assume that the profit shock ϵ is distributed according to a multivariate extreme value distribution, with known parameters:

Assumption 2. *The distribution of the profit shock is*

$$Pr\left(\epsilon_t < y\right) = G\left(y\right) = \exp\left\{-\exp\{-y-\gamma\}\right\}$$

for $\gamma = 0.577...$ (Euler's constant).

These two assumptions permit the computation of choice probabilities for any particular outcome :

Proposition 1. *Let any present time variable a at one period prior be written as a_{-1}, and one period in the future be written as a'. Given Assumptions 1 and 2, and grouping together the state variables as $s = \{p_{-1}, x_{-1}\}$, the probability of observing a particular exporter choice x^C conditional on state variables s and cost parameters β, $P\left(x^C | s, \beta\right)$, is:*

$$P\left(x^C | s, \beta\right) = \frac{\exp\left[\overline{\pi}\left(x^C, s, \beta\right) + \delta EV\left(x^C, s\right)\right]}{\sum_{\widehat{x} \in X} \exp\left[\overline{\pi}\left(\widehat{x}, s, \beta\right) + \delta EV\left(\widehat{x}, s\right)\right]} \tag{1.C..1}$$

where the function $EV\left(x, s\right)$ is the solution to the fixed point problem:

$$EV\left(x, s\right) = \int_{s'=0}^{\infty} \log\left\{\sum_{x' \in X} \exp\left[\overline{\pi}\left(x', s', \beta\right) + \delta EV\left(x', s'\right)\right]\right\} f\left(s' | s, x\right) \tag{1.C..2}$$

Proof. Let any present time variable a at one period in the past be represented as a_{-1}, and one period in the future be written as a'. Group the state variables together as $s = \{p_{-1}, x_{-1}\}$.

Theorem 1 in Rust (1987) states that, using Assumption 1, for the social surplus function defined as

$$S\left(\left[\overline{\pi}\left(s,\beta\right)+\delta EV\left(s\right)\right]\right) \equiv \int_{\epsilon} \max_{x}\left[\overline{\pi}\left(x,s,\beta\right)+\delta EV\left(x,s\right)\right] g\left(\epsilon\right) \tag{1.C..3}$$

the choice probability of any particular exporter choice x occurring can be written

$$P\left(x|s,\beta\right) = S_x\left(\left[\overline{\pi}\left(s,\beta\right)+\delta EV\left(s\right)\right]\right)$$

where G_x is the derivative of S with respect to $\overline{\pi}\left(x,s,\beta\right)$. Furthermore, the function $EV\left(x,s\right)$ can be written as the contraction mapping:

$$EV\left(x,s\right) = \int_{s'} S\left(\left[\overline{\pi}\left(s',\beta\right)+\delta EV\left(s'\right)\right]\right) f\left(s'|s,x\right)$$

Therefore, we need to compute the social surplus function S given the specific functional form of the density of ϵ.
The location parameter μ for a random variable ϵ with multivariate extreme value

distibution is defined such that μ satisfies:

$$Pr\left(\epsilon < y\right) = \exp\{-\exp\{-\left(y-\mu\right)\}\}$$

Additionally, the expectation of ϵ is $\mu+\gamma$, where γ is Euler's Constant. Following a procedure similar to the one in McFadden (1981), Assumption 2 means that the location parameter for the multivariate extreme value distibution of the profit shock ϵ is equal to $-\gamma$. This means that the expectation of ϵ is equal to 0, and we can rewrite the integral in (1.C.3) as:

$$\int_{\epsilon} \max_{x}\left[\overline{\pi}\left(x,s,\beta\right)+\delta EV\left(x,s\right)+\epsilon\left(x\right)\right] g\left(\epsilon\right) = \mathbb{E}_{\epsilon}\left\{\max_{x}\mu_x+\epsilon\left(x\right)\right\} \tag{1.C..4}$$

So the social surplus function will be the expectation of the expression inside the brackets.

For any n indepdent random variables, $\{\epsilon_1, ...\epsilon_n\}$:

$$\begin{aligned} Pr\left(\max\left\{\epsilon_1,...,\epsilon_n\right\} < y\right) &= Pr\left(\epsilon_1 < y, \ldots, \epsilon_n < y\right) \\ &= Pr\left(\epsilon_1 < y\right)\cdots Pr\left(\epsilon_n < y\right). \end{aligned}$$

Thus for any n independent random variables distributed according to the multivariate extreme value distubtion with location parameters $\mu_1, \ldots, \mu_n$, with cumulative distribution function in Assumption 2:

$$\begin{aligned}
Pr\left(\max\left\{\epsilon_1, ..., \epsilon_n\right\} < y\right) &= Pr\left(\epsilon_1 < y\right) \cdots Pr\left(\epsilon_n < y\right) = \prod_{i=1}^{n} \exp\left\{-\exp\left\{-\left(y-\mu_i\right)\right\}\right\} \\
&= \exp\left\{-\sum_{i=1}^{n} \exp\left\{-y\right\} \exp\left\{\mu_i\right\}\right\} \\
&= \exp\left\{-\left(\exp\left\{-y\right\} \exp\left[\log \sum_{i=1}^{n} \exp\left\{\mu_i\right\}\right]\right)\right\} \\
&= \exp\left\{-\exp\left\{-\left(y - \log \sum_{i=1}^{n} \exp\left\{\mu_i\right\}\right)\right\}\right\}
\end{aligned}$$

Thus the maximum of n random variables $\{\epsilon_i\}_{i=1}^{n}$ distibuted mulitvariate extreme value with location parameters $\{\mu_i\}_{i=1}^{n}$ is distributed multivariate extreme value with location parameter $\log \sum_{i=1}^{n} \exp\{\mu_i\}$. The expression inside the brackets in equation (1.C.4) is therefore distibuted multivariate extreme value with location parameter $-\gamma + \log \sum_{x \in X} \exp(\mu_x)$. Since the expectation of any random variable distibuted multivariate extreme value with location parameter μ is $\mu + \gamma$, the social surplus function from (1.C.4) can be written as:

$$\mathbb{E}\left\{\max_x \mu_x + \epsilon(x)\right\} = \log \sum_{x \in X} \exp(\mu_x) = \log \sum_{x \in X} \exp\left[\overline{\pi}(x, s, \beta) + \delta EV(x, s)\right]$$

Following Theorem 1 in Rust (1987), the derivative of the social surplus function is the choice probability:

$$\begin{aligned}
P\left(x^C | s, \beta\right) &= S_{x^C}\left(\left[\overline{\pi}(s, \beta) + \delta EV(s)\right]\right) \\
&= \frac{1}{\sum_{x \in X} \exp\left[\overline{\pi}(x, s, \beta) + \delta EV(x, s)\right]} \cdot \exp\left[\overline{\pi}\left(x^C, s, \beta\right) + \delta EV\left(x^C, s\right)\right]
\end{aligned}$$

, and the function EV satisfies the fixed point equation:

$$\begin{aligned}
EV(x, s) &= \int_{s'} S\left(\left[\overline{\pi}(s', \beta) + \delta EV(s')\right]\right) f(s'|s, x) \\
&= \int_{s'=0}^{\infty} \log\left\{\sum_{x' \in X} \exp\left[\overline{\pi}(x', s', \beta) + \delta EV(x', s')\right]\right\} f(s'|s, x)
\end{aligned}$$

as desired. $\square$

APPENDIX 1.D

Model Fit

In this appendix, I check how well the estimated parameters do at matching the underlying data used to generate those parameters. Compared to the size of the discrete choice problem, the simple model I estimate is unlikely to match specific importer-exporter outcomes exactly. Thus I check model fit in three areas: how well prices match, how well the percent of switching importers match, and how well the percent of city-switching importers match. I begin by comparing prices.

As can be seen in Table 1.D.1, the model with the estimated parameters underpredicts the true price index in the data. In most cases, the pattern is repeated at the industry level- in other words, each industry price index predicted by the model tends to be lower than its real-world counterpart. This is occurring for three reasons: first, the discrete choice model places no distinction on different sizes of the importers- as a precondition of solving the model, the fixed point problem (1.10) is solved assuming that any two importers with the same state will make the same decision. However, empirical results above show a statistically significant difference in the likelihood of switching based on importer firm size. Thus the model may predict a particular large firm to switch to a lower priced exporter, while in the data, this same firm is in fact less likely to do so. Secondly, the decision of which exporter to use is based on *expected prices* that are predicted with some error, rather than the true actual prices, again giving the potential for prices to be misaligned. Thus the true received price is not an object that I am trying to match through estimating parameters, and is rather an outcome based on a probability distribution. Finally, I discretize the price space into $N + 5$ intervals to estimate the model, applying the midpoint price for each interval, rather than actual price data. This introduces another dimension for the model to fall short.

Figures 1.D.1 and 1.D.2 present a separate summary measure: rather than summarizing 1000 outcomes for each firm, I can alternatively create the price index P across all firms and industries for each Monte Carlo run, and compare them. By either taking the weighted average of the price across firms in an industry (Figure D1), or the median price across firms in an industry (Figure 1.D.2), I can generate density plots. Again, as the above results also show, the model generally tends to underpredict the price index.

The results for switching and city switching are more straightforward. For each case, I simply calculate the overall number of firms in an industry predicted to switch for each Monte Carlo run, and take either the median or the mean of that industry percentage for each of 1000 runs. I then translate that into how many total firms are predicted to switch in each industry, and sum together across industries to create an overall measure of switching and city swiching behavior. It is clear to see that I match the percentage of firms switching extremely well. I match less well the number of firms switching city, underpredicting the true number by approximately 10%. This is likely because predicting the city puts more pressure on the model of exporter choice to pick the exporter more correctly, while the overall switching percentage does not have to match the chosen exporter in the data as well.

APPENDIX 1.E

Potential for Serial Correlation

In Section 1.3, I model the importer's decision to choose a particular supplier as a dynamic discrete choice model with switching costs, where one-period profits-including an i.i.d. error term- take the following form:

$$\overline{\pi}_t^m\left(x_t^m, \boldsymbol{\beta}\right) + \epsilon_{x,t}^m = \xi \ln \lambda_{x,t} + \beta_p \mathbb{E}\left[\ln p_{x,t}^m\right] - \beta_x \mathbb{1}\{x_t^m \neq x_{t-1}^m\} - \beta_c \mathbb{1}\{c_t^m \neq c_{t-1}^m\} + \epsilon_{x,t}^m \tag{1.E..1}$$

One problem with the above equation is it excludes the possibility of serial correlation in the error term. For example, if an importer chooses exporter x two periods in a row, the model would interpret that as evidence for state dependence, when it could be the case that importer has some characteristic- constant over time- that makes them prefer exporter x in both periods. If the results are being driven by this heterogeneity, then the switching cost estimates might be overestimated.

In order to account for such bias, it is possible to allow an importer-exporter specific term to enter into the profit equation:

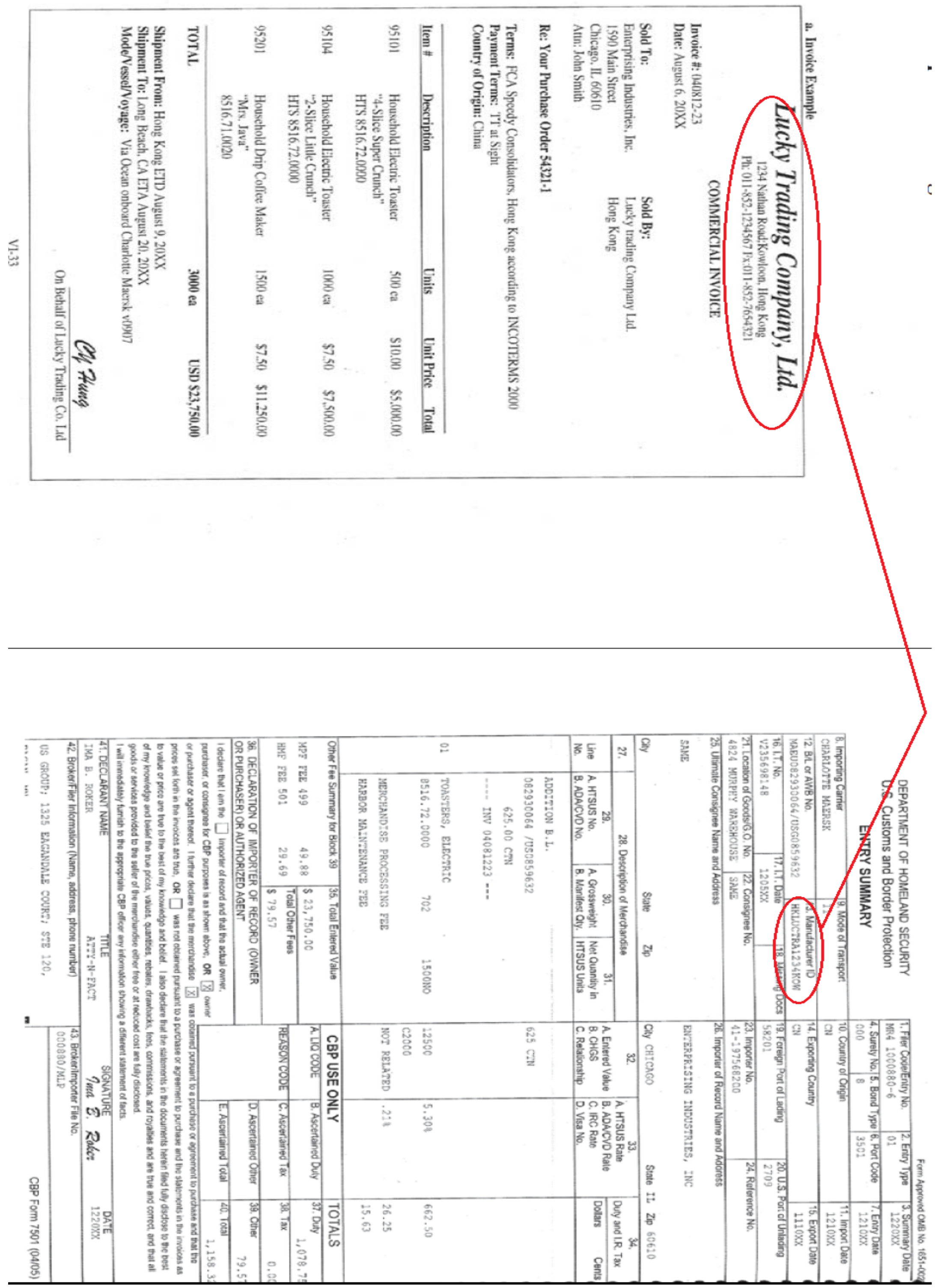
$$\overline{\pi}_t^m\left(x_t^m, \boldsymbol{\beta}\right) + \epsilon_{x,t}^m = \xi \ln \lambda_{x,t} + \beta_p \mathbb{E}\left[\ln p_{x,t}^m\right] - \beta_x \mathbb{1}\{x_t^m \neq x_{t-1}^m\} - \beta_c \mathbb{1}\{c_t^m \neq c_{t-1}^m\} + \alpha_x^m + \nu_{x,t}^m \tag{1.E..2}$$

A reduced form way to account for this issue is to include *lagged quality* $\lambda_{x,t-1}$ in the profit equation. The idea is since lagged quality does not affect current profits (something that is straightforward to test empirically), but is both exporter and importer specific, it could be included as the α term in the above equation.

Alternatively, the α term in Equation (1.E.2) can be estimated as an additional set of parameters via the maximum likelihood process. Each importer would have a particular realization from the distribution of the exporter's α. With an average of 35 exporters per product, this would mean 35 new state variables to include in the dynamic programming problem (a 35-dimensional random effect). The brute force method would be to calculate the distibutions of these 35 separate state variables (for example α_{MEAN} and α_{SD} for each exporter $x = 1, ...35$) as an additional loop in the maximum likelihood problem, as the dynamic programming problem would be different for each vector of α realization. Ackerberg (2009) presents a method to simplify the problem through use of importance sampling to reduce the computation time for such a problem.

A simplifying solution would be to assume that the individual realization of α_x^m is not observed until the match is actually made- a "limited memory". This would increase the state space by only one variable, and we would be using the data to estimate what those realizations must have been for the observed choices to have been made. In this case, the α term in Equation (1.E.2) would be importer-exporter-relationship-time specific. This would also account for the possiblity of serial correlation in the error term of Equation (1.E.1).

Figure 1.A.1: Sample Invoice



Note: Exporter specific information and location information from the invoicing party is extracted from trade data.

Table 1.A.1: Analysis of MIDs as Constructed from China Industrial Production Data, Selected Industries

Panel A: Uniqueness of the "MID", 2005

Industry (CIC)	# of Exporters	# of "MID"s	%
CIC 3663	39	38	97.4
CIC 3689	27	26	97.3
CIC 3353	37	37	100
CIC 3331	35	35	100
CIC 4154	74	73	98.6

This panel uses name, address, and city information from China NBS firm data to construct a "MID" for each firm, according to the rules laid out in U.S. CBP Form 7501. In constructing the name of the firm in English, I use the Hanyu Pinyin romanization of Chinese characters, with two to three characters per word of the English name. The second column states the number of firms with positive export values in the given industry in 2005. The third column states the number of unique constructed "MID"s.

Panel B: Uniqueness of the City Code

Industry (CIC)	# of Cities	# of City Codes,2005	%
CIC 3663	22	21	95.5
CIC 3689	15	14	93.3
CIC 3353	28	24	85.7
CIC 3331	15	13	86.7
CIC 4154	19	18	94.7

Panel B uses city information from China NBS firm data to construct city information as found in the MID, where only the first three letters of city are given. The second column states the true number of cities with at least one exporting firm in the data from 2005, while the third column states the number of unique city codes.

Panel C: Changes in the "MID" over Time, 2005-2006

Industry (CIC)	# of Exporters	# of with Identical "MID"	%
CIC 3663	33	33	100
CIC 3689	26	26	100
CIC 3353	31	28	90.3
CIC 3331	20	17	85.0
CIC 4154	63	62	98.4

Panel C uses name, address, and city information from China NBS firm data to track whether constructed "MID"s change over time for the same firm, identified here using the *"faren daima"* firm identifier from the NBS data. The second column states the number of exporting firms found in both 2005 and 2006, while the third column states the number of firms that have identical "MID"s in both 2005 and 2006.

Source: China National Bureau of Statistics.

Table 1.A.2: List of Industries Used in Counterfactuals

HS6 Code	Description	Share
291560	Butyric Acid, Valeric Acid, Their Salts and Esters	0.31%
291631	Benzoic Acid, Its Salts and Esters	0.25%
293629	Other Vitamins and Their Derivatives (Unmixed)	0.86%
340120	Soap in other forms	0.66%
392020	Other Plates, Sheets, Film, Foil, Tape, Strip of Propylene Polymers (Non-cell.)	0.83%
481810	Toilet paper	1.02%
481960	Box files, letter trays, storage boxes and similar articles, used in offices, shops	0.55%
490300	Children's picture, drawing or coloring books	0.86%
520831	Plain Woven Fabrics, Cotton (Cotton 85% or More; Dyed; Not >100g/m2)	0.72%
560312	Nonwovens of man-made filament,>25g/m2	0.87%
570210	Kelem, Schumacks, Karamanie and Similar Hand-woven Rugs	0.65%
580639	Other Narrow Woven Fabrics of Other Textile Materials	0.62%
591190	Other Textile Products and Articles, for Technical Use	1.07%
610432	Women's or Girls' Jackets of Cotton, Knitted or Crocheted	0.66%
610791	Men's or Boys' Bathrobes, Dressing Gowns, of Cotton, Knitted or Crocheted	1.84%
620339	Men's or Boys' Jackets, Blazers, of Other Textile Materials	1.23%
621230	Corsets	0.59%
621490	Shawls, Scarves, Mufflers, Mantillas, Veils, of Other Textile Materials	0.15%
640219	Other Sports Footwear, Outer Soles and Uppers of Rubber or Plastics	7.93%
640340	Other Footwear, Incorporating Protective Metal Toe-cap	10.65%
650699	Headgear of Other Materials	0.23%
650700	Headbands, Linings, Covers, Hat Foundations, Hat Frames, for Headgear	0.13%
670411	Complete Wigs of Synthetic Textile Materials	1.65%
730722	Threaded elbows, bends and sleeves, of Stainless Steel	0.18%
730830	Doors, windows and their frames and thresholds for doors, of Iron or Steel	0.87%
731814	Self-tapping screws of Iron or Steel	3.11%
731930	Other pins of Iron or Steel	0.21%
820310	Files, rasps, and similar tools	0.11%
820890	Other (including parts) (Knives and Blades for machines and appliances)	X
830300	Armored/ reinforced safes, strong-boxes, safe deposit lockers, of base metal	4.44%
830990	Stoppers, Caps, Lids, Seals, Other Packing Accessories, of Base Metal	0.61%
841320	Hand Pumps for Liquids	0.18%
841360	Other Positive Rotary Displacement Pumps	0.42%
841370	Other Centrifugal Pumps	2.13%
841420	Hand or Foot Operated Air Pumps	0.46%
841850	Refrigerating, Freezing Chests, Cabinets, Display Counters, Show-cases & Sim.	2.46%
848110	Pressure-reducing Valves	X
850650	Lithium primary cells and primary batteries	0.82%
850910	Vacuum Cleaners, With Self-contained Electric Motor	14.30%
850940	Food Grinders and Mixers; Fruit or Vegetable Juice Extractors	9.81%
853641	Relays, for a Voltage Not Exceeding 60v	2.01%
870893	Clutches and parts thereof	1.74%
871110	Motorcycles, Side-cars, Reciprocating Engine, cylinder cap. not >50 cc	3.33%
871120	Motorcycles, Side-cars, Reciprocating Engine, cylinder cap. >50 cc not 250 cc	7.10%
900580	Monoculars, Other Optical Telescopes; Other Astronomical Instruments	1.99%
902910	Revolution counters, production counters, taximeters, odometers, etc	0.60%
920590	Other wind musical instruments	0.60%
950631	Golf Clubs, Complete	4.60%
960321	Tooth Brushes	1.10%
960910	Pencils and Crayons, With Leads Encased in a Rigid Sheath	2.10%

These shares are the percent of import value compared to the total among these 50 industries. The number of importing firms in HS 848110 is too few to report importing information: the combined value share of HS 848110 and 820890 is 0.37%.

Figure 1.B.1: Year-to-Year "Staying" (New Definition) Percentages of U.S. Importers from China

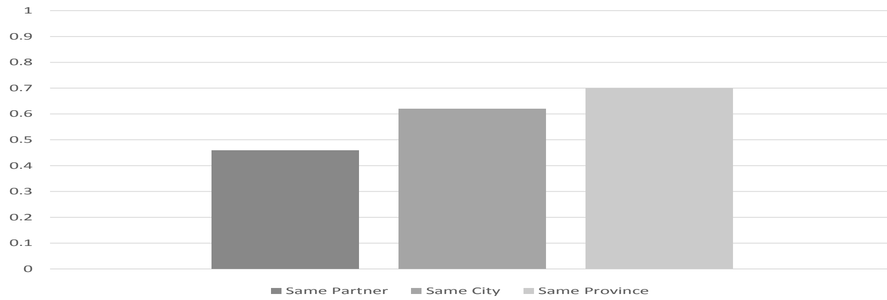


Figure 1.B.2: Year-to-Year "Staying" Percentages of U.S. Importers from China, Manufacturers Only

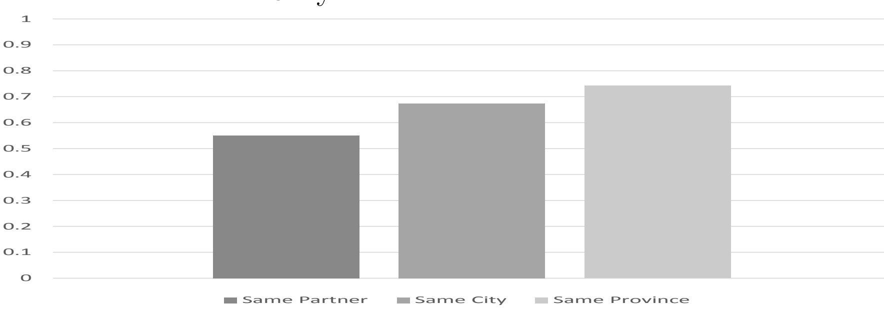


Figure 1.B.3: Year-to-Year "Staying" Percentages of U.S. Importers from China, Firm-HS6

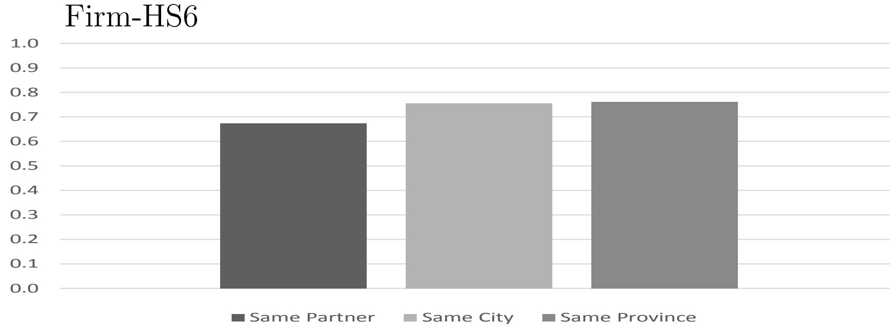


Figure 1.B.4: Year-to-Year "Staying" Percentages of U.S. Importers from China, Individual Years

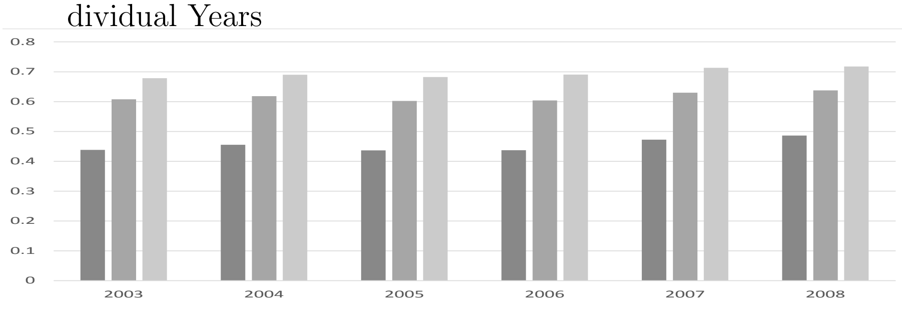


Table 1.B.1: Determinants of Supplier Stay/Switch Decision

Dependent Variable: Stayed with Chinese Exporter Year-to-Year, 2005-2006

	(1)	(2)	(3)	(4)
Log Price				
1st Decile	-0.0065	0.0176**	0.0143*	0.0137*
	(0.007)	(0.007)	(0.007)	(0.007)
2nd Decile	-0.0115	0.0041	0.0044	0.0050
	(0.008)	(0.008)	(0.008)	(0.008)
3rd Decile	-0.0024	0.0002	0.0003	0.0001
	(0.008)	(0.008)	(0.008)	(0.008)
4th Decile	-0.0018	-0.0007	-0.0004	-0.0007
	(0.007)	(0.007)	(0.007)	(0.007)
6th Decile	-0.0128*	-0.0131*	-0.0132*	-0.0132*
	(0.007)	(0.007)	(0.007)	(0.007)
7th Decile	-0.0097	-0.0088	-0.0086	-0.0088
	(0.008)	(0.008)	(0.008)	(0.008)
8th Decile	-0.0141*	-0.0126*	-0.0135*	-0.0136*
	(0.008)	(0.008)	(0.007)	(0.007)
9th Decile	-0.0218**	-0.0158**	-0.0170**	-0.0175**
	(0.007)	(0.007)	(0.007)	(0.007)
10th Decile	-0.0414***	-0.0256***	-0.0285***	-0.0293***
	(0.007)	(0.008)	(0.007)	(0.007)
Log Supplier Size		0.0360***	0.0671***	0.0671***
		(0.001)	(0.001)	(0.001)
Supplier Age		-0.0020***	-0.0028***	-0.0026***
		(0.000)	(0.000)	(0.000)
Importer Size			-0.0410***	-0.0396***
			(0.002)	(0.002)
Constant	0.4547***	0.0699***	0.1768***	0.1530***
	(0.005)	(0.012)	(0.013)	(0.014)
Entry Year FE	No	No	No	Yes
N	93,530	93,530	93,530	93,530
R^2	0.13	0.14	0.15	0.15

Notes: Robust standard errors clustered at the HS10 level in brackets. *** significant at the 1% level, ** significant at the 5% level. HS10 fixed effects are included. The sample is the universe of U.S. importers (HS10 product code and fim combination) from China who are found 2005-2006. The dependent variable is equal to 1 if the U.S. importer had the largest (plurality) share of its total import value from the same Chinese supplier in both years, and equal to 0 if not. Log price is the log average unit value across transactions with its majority partner in the previous year, standardized across products by subtracting the HS10 mean and dividing by the standard deviation. Supplier size is the total estimated exports of a Chinese supplier in the HS10 product code in 2005, based on cross-section summation of total exports to the U.S. Supplier Age is calculated using the first year the Chinese supplier appears in the U.S. customs data, and subtracting it from 2005. Importer size is the total size of imports in that HS10 product code in 2005 for any U.S. firm. Importer Entry Year is the first year a U.S. importers is found importing from China. Any importer that has the same share of imports from two separate Chinese suppliers is dropped.

Table 1.B.2: Determinants of Supplier Stay/Switch Decision

Dependent Variable: Stayed with Chinese Exporter Year-to-Year, 2005-2006

	(1)	(2)	(3)	(4)
Log Price	-0.0108***	-0.0116***	-0.0121***	-0.0121***
	(0.002)	(0.002)	(0.002)	(0.002)
Log Supplier Size		0.0290***	0.0518***	0.0514***
		(0.001)	(0.002)	(0.002)
Supplier Age		-0.0017***	-0.0024***	-0.0022***
		(0.000)	(0.000)	(0.000)
Importer Size			-0.0269***	-0.0251***
			(0.002)	(0.002)
Constant	0.4425***	0.1392***	0.1823***	0.1560***
	(0.000)	(0.011)	(0.011)	(0.013)
Entry Year FE	No	No	No	Yes
N	93,530	93,530	93,530	93,530
R^2	0.13	0.14	0.14	0.14

Notes: Robust standard errors clustered at the HS10 level in brackets. *** significant at the 1% level, ** significant at the 5% level. HS10 and year fixed effects are included. The sample is the universe of U.S. importers (HS10 product code and fim combination) from China who are found two years in a row. The dependent variable is equal to 1 if the U.S. importer had the largest (plurality) share of its total import value from the same Chinese supplier in both years, and equal to 0 if not. Log price is the log average unit value across transactions with its majority partner in the previous year, standardized across products by subtracting the HS10 mean and dividing by the standard deviation. Supplier size is the total estimated exports of a Chinese supplier in the HS10 product code in 2005, based on cross-section summation of total exports to the U.S. Supplier Age is calculated using the first year the Chinese supplier appears in the U.S. customs data, and subtracting it from 2005. Importer size is the total size of imports in that HS10 product code in 2005 for any U.S. firm. Importer Entry Year is the first year a U.S. importers is found importing from China. Any importer that has the same share of imports from two separate Chinese suppliers is dropped.

Table 1.D.1: Model Fit

	Data	Median over 1000 runs	%
Price Index			
Weighted Average	84.6239	76.4979	90.4
Median	66.1725	61.7019	93.2

	Data	Industry Median	%	Industry Mean	%
Total Switching Partner	714	711	99.6	708.85	99.3
Total Switching City	416	469	112.7	469.76	112.9

Notes: Objects computed by the model simulated with the estimated parameters are compared to the same objects in the data. To compute the Price Index, I first take the median received price across 1000 simulations for each importer. I then either weight each importer by its industry share, and sum up ("Weighted Average") or I simply compute the median across importers in an industry. I then apply industry weights based on total trade among along simulated industries to make an aggregate price index. The switching and city switching figures are the number of importers switching partner or city in the data compared to either the mean number of firm switching/city switching for each industry, or the median number of firms switching/city switching for each industry.

Figure 1.D.1: Price (Weighted Average) Kernel Density Plot

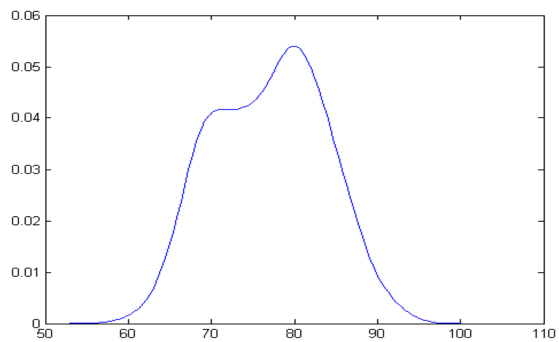
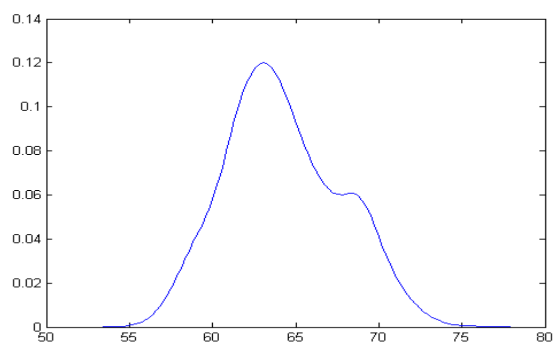


Figure 1.D.2: Price (Median) Kernel Density Plot



Notes: These figures are the analogue of the weighted average and median price kernel density plots described in Appendix 1.D.

APPENDIX 2.A

Data Appendix

In this appendix, we describe how we created a baseline dataset of offshoring plants.

Linking TAA to the Business Register

The operational information of manufacturing establishments used in this paper is obtained from the Longitudinal Business Database (LBD) and Annual Survey and Census of Manufactures (ASM/CMF). The information on offshoring events is obtained from the petition data of the Trade Adjustment Assistant program (TAA). Unfortunately, direct matching of these two data are not possible because TAA petition data do not have establishment or firm identifiers. The information that can identify a particular establishment is company name and address (state, city, street address, and zip code), but neither the LBD nor the ASM/CMF contains address information. For this reason, we first match the TAA petition data to the Business Register (BR) using name and state, then match the merged data to LBD using plant identifiers. The Business Register was formerly known as the SSEL.

Name and address matching between TAA petition data and the BR is imperfect because TAA petitions are filed by workers and unions, rather than the authority that generally responds to various surveys conducted by the U.S. Census Bureau. The company names and address reported in the TAA petition form is not necessarily the official name or address. Also, there is no rule against using P.O. Box address for the purpose of survey response for both TAA petitions and any survey from the Census Bureau. To avoid being too restrictive, we use only name and state as matching criteria. Company names have inconsistencies and ambiguities too. The majority of the issues here stems from variations in the legal endings of companies such as 'Limited,' 'Incorporated,' 'Corporation.' We drop those legal endings before merging. Other corrected issues, where possible, are numerics (e.g. '1' v. 'one'), other abbreviations (mfg, tech, bros, and so on), and simple typos.

We made separate merging for petitions with different years. Since our petition dataset contains petitions with impact date from 1999 to 2006, we performed merging of eight separate years. TAA petitions with each impact year is merged with four BR years surrounding the impact year; more specifically, two years prior to the impact year, impact year, and one year after. For instance, petitions with impact year of 2003 is merged with BR files from 2001, 2002, 2003, and 2004. Using additional matching criteria (zip code), we selected the year of the best match among these four years merged and obtain plant identifiers from the corresponding BR files. Table A1 summarizes the matching rate for each impact year for aggressive matching. Out of total of 19,603 petitions in our sample, 13,645 are matched to BR yielding a matching rate of 69.61%. Among the matched petitions, 5,167 petitions are identified as offshoring events.

Linking to LBD

In order to make a longitudinal link for surveys of different years for one establishment, we use the LBD. For each petition we match the petition information to the LBD file of the year of best BR match rather than impact year because the plant identifiers of the best BR year are most reliable. This BR-LBD matching rate is 76.41% for all sample. Since the first impact year of the petition data is 1999, and it is matched to one of four years surrounding the impact year, the range of BR years thus goes from 1997 to 2007. Merging is carried out for each year separately, then was appended.

Once the establishment ID is retrieved for all offshoring events, we build the event window of 13 years; six years before and six years after the event. Before we construct the event window, we first deal with the issue of multiple petitions per establishment. Some establishments file the petition more than once over time. All petitions are not necessarily filed for the same reason. We give priority to offshoring event, import-related event, and denied event. Among the petitions certified for the same reason, or denied petitions, we keep the first event. For instance, if a plant A is certified for import-related reasons in 2001, for an offshoring-related reason in 2003, and denied in 2004, we keep the 2003 event of offshoring. If a plant is certified for offshoring in 2002 and 2004, then we keep the 2002 event. Multiple offshoring events for a firm in the same year are treated as one offshoring event for the firm since all analysis are carried out at the firm-level. In construction of pseudo firms (aggregation of non-offshored plants of offshoring firms), all offshored plants are dropped. Table **??** summarizes the total number of events after this sorting with petitions matched to LBD. At this stage, we have 3,400 offshoring events, 1,618 import-related events, and 3,835 denied petitions to be total of 8,853 petitions.

Building firm-level links

A firm link is built with the variable firmid in LBD. For each year, we group all establishments by firmid, including non-manufacturing units. For each firm, we construct three firm-level variables. We first construct firm-level employment by aggregating all establishment-level employment. Average wage rate is constructed by dividing the aggregate payroll by aggregate employment. Lastly firm-level 3-digit SIC code is selected. We aggregate employment by industry within the firm, then select the 3-digit SIC industry that has the largest employment in the firm. Offshoring firm is selected by matching the firmid of the offshored establishment to the firm-level data constructed as described above. The matching is obtained for the year before the offshoring event. We build the event window of 13 years by adding six years before and after the offshoring event.

Table 2.A.1: Results of Aggressive Matching Procedure of TAA to Business Register

Impact Year	Total # of Petitions	# Certified	# Offshored	# Matched	Matching Rate (%)	Among Matched Petitions: Offshoring	Import Competition	Denied
1999	998	328	200	803	80.46	153	118	532
2000	2,593	1,489	833	2,267	87.43	702	658	907
2001	3,329	1,094	794	2,090	62.78	810	275	1,005
2002	3,825	1,757	1,211	2,585	67.58	990	476	1,119
2003	2,505	1,266	887	1,718	68.58	733	271	714
2004	2,545	1,320	876	1,614	63.42	620	320	674
2005-6	3,808	1,853	1603	2,568	67.44	1,159	217	1,192
Total	19,603	9,107	6,404	13,645	69.61	5,167	2,335	6,143

Table 2.A.2: Counts of Offshoring Events Matched to LBD

Impact Year	Total	# Offshoring	# Import Competition	# Denied
1999	503	96	82	325
2000	1,396	423	404	569
2001	1,269	490	162	617
2002	1,946	784	381	781
2003	1,125	492	202	431
2004	1,009	383	233	393
2005-6	1,606	732	154	719
All	8,853	3,400	1,618	3,835